Operational performance of two-stage food production systems

Process interactions and capacitated storage

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The work presented in this thesis was carried out at the Production Systems Design group in the Faculty of Management and Organization at the University of Groningen. I want to thank its current *and* past members for creating a pleasant environment to work in. Specifically, I want to thank Chetan, Gert, and Peter for their part in this.

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Renzo Akkerman
Groningen, November 2006

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CONTENTS

CHAPTER 1
Introduction

The food-processing industry is an important industrial sector. In terms of turnover and employment, it is the largest manufacturing sector in the European Union (CIAA, 2005). As an illustration of the sectors' size, some key indicators for the Dutch food-processing industry can be found in Table 1.1. With almost 25% of the total industrial turnover, it is a major part of the economy. In the last decade, we have seen several important developments in the food sector:

- In the European Union, food retailing has become more and more concentrated and is expected to further concentrate (Dobson *et al.*, 2001). For food producers, Dobson *et al.* argue, this can result in fiercer competition, where retail chains dictate terms of sale and food manufacturers see their margins get squeezed.
- An increasing focus on food safety (*e.g.*, Griffith, 2006), leading to more stringent legislation. Examples can be found in traceability requirements or HACCP implementation. From a food producers' viewpoint, this results in additional production complexity.
- The increasing importance of sustainable production (CIAA, 2002). Organizations are not only held responsible for the quality of their products, but also for the environmental performance (in terms of waste, but also ecological production) of their production system (see *e.g.*, Bansal and Roth, 2000).

Table 1.1. Characteristics of the Dutch food-processing industry (CBS, 2006).

Characteristic	**Value (2003)**	**Share of total industry**
Number of companies	4,785	10.43%
Number of employees	118,000	16.14%
Turnover	EUR 53,841 million	24.10%
Financial result	EUR 3,708 million	28.94%

In order to keep a competitive advantage in light of these developments, food manufacturers are increasingly interested in improving the efficiency of their operations. Subsequently, good operations management (OM)[1] has never been more important in the food-processing industry.

1.1 Operations management in the food industry

In contrast to discrete industries, process industries have had relatively less attention in the OM literature. Over the last 25 years, a few authors emphasized the differences between discrete and process industries (*e.g.*, Taylor *et al.*, 1981; Fransoo and Rutten, 1994), but only recently, the research efforts concerning process industries seem to be increasing (*e.g.*, Berry and Cooper, 1999; Dennis and Meredith, 2000; Flapper *et al.*, 2002). This is also reflected in a recent special issue of the Journal of Operations Management on OM in the process industries(Van Donk and Fransoo, 2006). However, given the industry's size, research attention is still lacking behind.

As an important sector within the process industries, the food-processing industry has had relatively little attention within the literature on process industries. It was also noticed by several other authors, because in recent years, we have seen that a number of areas within the food-processing industry have been explored, leading to interesting contributions to the field. Below, some of these contributions will be outlined to give an impression of recent literature on OM in food processing, and to set the scene for the research questions addressed in this thesis.

- Hill and Scudder (2002) explore the use of electronic data interchange (EDI) in the food industry. Based on survey results, they state that firms see EDI mainly as a tool for improving efficiency rather than supply chain integration.

- As a result of the increasing competitiveness, food producers who traditionally followed make-to-stock (MTO) strategies, have partly moved to make-to-order (MTS) strategies. This issue is discussed by Soman (2005), who develops tools and models to gain insights in the planning and control of production environments in mixed MTO-MTS situations.

[1] According to the APICS dictionary, operations management can be defined as "the field of study that focusses on the effective planning, scheduling, use, and control of a manufacturing or service organization through the study of concepts from design engineering, industrial engineering, management information systems, quality management, production management, inventory management, accounting, and other functions as they affect the organization" (Cox and Blackstone, 2002)

- Based on the current importance of food safety, there is an increasing possibility of product recalls. This requires food producers to be able to trace products efficiently. In this setting, Dupuy *et al.* (2005) discuss traceability and batch dispersion to be able to minimize the quantity of recalls.

- In a study on the implementation of Advanced Planning and Scheduling systems in the fresh food industries, Lütke Entrup (2005) concludes that several issues are important for all the case studies he presents. Among characteristics like intensive supply chain collaboration and the importance of quality management, he identifies product shelf life as the most distinguishing characteristic of the fresh food industry. In a related publication, Lütke Entrup *et al.* (2005) present a number of mathematical models for planning and scheduling in yoghurt production.

- After describing the increasing need for flexibility in the food-processing industry, Van Wezel (2001) notices an inconsistancy between the flexibility of food production systems and the flexibility that is required by the market. He discusses several production planning issues, such as hierarchical planning and computer support, in the light of flexibility. In Van Wezel *et al.* (2006), the discussion on flexibility is continued, and the study shows that existing production planning approaches are often not able to make the most of the available flexibility in the production process.

- A growing concern for the environment is leading the industrial sector to adopt waste minimization programmes. For the food sector, (Bates and Phillips, 1999) demonstrate the financial and environmental benefits of such programmes. Following this development, Kleindorfer *et al.* (2005) see numerous possibilities and challenges for sustainable OM in general. Specifically for process industries, Flapper *et al.* (2002) reviewed planning and control of rework, an important aspect of sustainable operations.

It is interesting to note that also from the field of food engineering — which is normally more oriented towards food properties and chemical engineering— there seems to be a growing interest in OM-related topics, illustrated by a recent special issue of the Journal of Food Engineering (Tarantilis and Kiranoudis, 2005).

Obviously, this is by no means an exhaustive review of OM research in the food-processing industry. It does, however, show some interesting recent

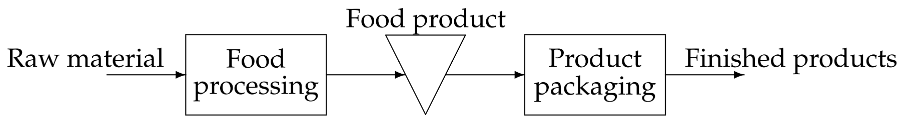

Figure 1.1. Two-stage food production system with intermediate storage.

developments, and illustrate several important characteristics of the current food-processing industry —*i.e.*, the focus on production efficiency, lead time reductions, a rising concern for food quality, the importance of shelf life, the need for flexibility, and an increasing concern for sustainable production.

Next to the described developments, the food-processing industry has a specific set of product and process characteristics (*e.g.*, perishable goods, divergent product structure). These characteristics have a significant impact on the management of operations. Concerning the process characteristics, food production typically concerns two production stages: processing and packaging. Between these stages, the unpackaged food product can normally be stored in intermediate storage tanks or silos (see Figure 1.1 for an illustration). For developments in OM in the food industry, this two-stage setting with capacitated intermediate storage is an important underlying process configuration. Processing and packaging are often two distinct production types (the latter concerns discrete units, while the former concerns a continuous product flow), which results in seperate —though dependent— OM decisions. This especially concerns the intermediate storage, as the interaction between the two stages reveils itself there.

Concluding, we can say that —despite the described recent developments— there is still little research on OM in the food-processing industry, given its importance. Also, numerous industry-specific characteristics are involved in a focus on efficiency and sustainability. This increases the importance of OM in the food-processing industry.

1.2 Research objectives

From the recent attention in the literature, we learn that there are numerous research topics concerning OM in the food-processing industry. Production managers in this industry still have numerous questions concerning the management of their operations. Most of these questions have to do with industry-specific characteristics (such as limited shelf life and volatile demand patterns) and their interaction with OM decisions. This thesis aims to contribute to the knowledge on OM in food processing. The main aspect of OM discussed in this thesis is production planning and control (PPC), but the included papers also relate to other OM aspects such as quality management, inventory management, and sustainability.

More specifically, this thesis focusses on two-stage food production systems with capacitated intermediate storage (see Figure 1.1). Within these systems, we study the interations between industry-specific characteristics and OM issues. In Chapter 2 to 6 of this thesis, several aspects of this overall theme are addressed. Every chapter depends on industry-specific characteristics, and addresses one or more OM issues in light of these characteristics. In the following section, the research questions addressed in this thesis are discussed in more detail.

1.2.1 Research questions

As could be seen in Figure 1.1, typical two-stage food production systems have intermediate storage possibilities between the processing and packaging stage. This storage is normally constrained in capacity and time. Capacity constraints are found in the form of a limited number of tanks or silos that have to be shared by various products. Time constraints follow from the (aforementioned) limited shelf life of food products.

In practice, the implications of these different storage constraints are not always straightforward. It is often hard to decide on the number of tanks needed for intermediate storage, or whether or not storage should be dedicated, and how such decisions influence production performance. This brings us to the first research question:

RQ1 What are the implications of capacity- and time-constrained intermediate storage on production performance?

Typical for the food-processing industry are introductions of new products, promotions and special (export) orders following from tenders. This can result in a high product mix variability. In addition, the current competitive market often requires extremely short lead times. The influence of these demand characteristics on production performance is not clear, and this results in the following research question:

RQ2 What are the performance implications of demand characteristics like high product mix variability and lead time reductions?

The final research question addresses the issue of product losses. Due to economical and environmental requirements, the reduction of product losses is important in improving profitability and sustainability of food production systems. In most cases, product losses are seen as a direct result of technological characteristics of the production system, but the interactions between the process configuration and PPC issues also plays an important role. However, the effects of planning decisions and production parameters are not straightforward, and this leads us to the following research question:

RQ3 How do planning decisions and process configurations influence the realization of product losses?

Next, we will describe how these research questions are dicussed in the remainder of this thesis.

1.2.2 Thesis outline

As industry-specific characteristics have a central place in this research, the thesis starts with a detailed discussion of the characteristics of the food-processing industry in Chapter 2. Based on previous research and several case studies, a specific combination of product and production characteristics for the food-processing industry is presented. To be able to relate these characteristics to OM and PPC issues, Chapter 2 also develops a framework to analyze planning and scheduling in the food-processing industry. The so-called context-based analysis methodology presented is based on decomposition of the production process and decomposition of the planning and scheduling task. It is intended to understand, describe, and structure planning and scheduling problems and the related organisational structures and information flows.

Chapter 3 starts discussing research question 1, by analysing the performance of several basic scheduling and sequencing rules under the mentioned capacity and time constraints on intermediate storage. The chapter aims to improve the understanding of the implications of such storage constraints in two-stage food production systems.

The current competitive market often requires extremely short lead times, which makes prioritization of products in planning and scheduling unavoidable. This often includes the dedication of intermediate storage capacity. In Chapter 4, this question is addressed and because the prioritization involves dedication of intermediate storage, the resulting paper contains insights on research question 1 and 2.

Next, Chapter 5 addresses the performance implications of product mix variability with correlated demand (relating to research question 2). An important aspect of the analysis in this chapter is that the correlations are defined on two dimensions: product types and package types. This resembles the two-stage production, where ach of these two stages determines one of the defining characteristics of the end product.

Subsequently, research question 3 is discussed in Chapter 6, where the importance of planning in the realisation of product losses is emphasized and a research framework and a decision tool for reduction of product losses are developed. The research famework presented in this chapter is also applied in a case study in the dairy industry, where an Excel-based tool is able to significantly reduce the planning-related product losses. Furthermore, it clarifies the interactions between processing, packaging, and intermediate storage.

Finally, the thesis concludes with an overview of the results in Chapter 7. The conclusions from the individual papers are summarized, and possible directions for further research are outlined.

1.3 Included publications

The chapters in this thesis are all papers that are either published, accepted for publication, or under review for journal publication. This means that all of these chapters are readable as individual contributions, but it does not mean they are not related to each other. The chapters contain the following papers (with corresponding chapter numbers):

2 – Renzo Akkerman and Dirk Pieter van Donk (2006), *Analysing scheduling in the food-processing industry: Structure and tasks*, Cognition, Technology & Work, accepted for publication.

3 – Renzo Akkerman, Dirk Pieter van Donk, and Gerard Gaalman (2006), *The influence of capacity- and time-constrained intermediate storage in two-stage food production systems*, International Journal of Production Research, accepted for publication.

4 – Renzo Akkerman and Dirk Pieter van Donk (2006), *Product prioritization in a two-stage food production system with intermediate storage*, International Journal of Production Economics, accepted for publication.

5 – Renzo Akkerman and Dirk Pieter van Donk (2006), *Product mix variability with correlated demand in two-stage food manufacturing with intermediate storage*, International Journal of Production Economics, accepted for publication.

6 – Renzo Akkerman and Dirk Pieter van Donk (2006), *Development and application of a decision support tool for reduction of product losses in the food-processing industry*, Journal of Cleaner Production, accepted for publication.

CHAPTER 2

Context-Based Scheduling

Published as:

R. AKKERMAN AND D.P. VAN DONK (2006), *Analysing scheduling in the food-processing industry: Structure and tasks*, Cognition, Technology & Work, accepted for publication.

Abstract

Production scheduling has been widely studied in several research areas, resulting in a large number of methods, prescriptions, and approaches. However, the impact on scheduling practice seems relatively low. This is also the case in the food-processing industry, where industry-specific characteristics induce specific and complex scheduling problems. Based on ideas about decomposition of the scheduling task and the production process, we develop an analysis methodology for scheduling problems in food processing. This combines an analysis of structural (technological) elements of the production process with an analysis of the tasks of the scheduler. This helps to understand, describe, and structure scheduling problems in food processing, and forms a basis for improving scheduling and applying methods developed in literature. It also helps in evaluating the organisational structures and information flows related to scheduling.

2.1 Introduction

Production scheduling is a widely studied subject in different research areas such as production and operations management, operations research (OR), artificial intelligence (AI), and cognitive sciences (CS). These research areas contain elements like modelling, analysing, and simulating the decision making process involved. It has focused on topics like algorithmic approaches, organizational problems, and information systems analysis.

In spite of all this research into scheduling, it seems to have had relatively little impact on production practice, where the use of scheduling systems and methods remains rare (McKay *et al.*, 2002). This is also the case in the food-processing industry, where industry-specific characteristics make scheduling a hard, but important, issue (*e.g.*, Jakeman, 1994). In this paper, we focus on food processing, being a significant part of the total industry that has received relatively little attention in scheduling research.

The lack of use in practice is, according to McKay *et al.* (2002), mainly because of the myopic nature of scheduling research. It mostly deals with simplified situations or only parts of a situation. Moreover, according to Crawford *et al.* (1999), scheduling is difficult to study because it can only be thoroughly investigated in the environment in which it is normally found: a complex, dynamic manufacturing environment. This also emphasizes the need for industry-specific instruments for scheduling. In our view, the complexity is mostly due to the fact that scheduling is often an unstructured issue, where the basic scheduling problems are interconnected with problems around organizational responsibilities and information flows.

Furthermore, the scheduling environment in food is complicated due to reasons like changing product mixes and incremental changes to the production system. Together with the unstructured nature of scheduling, this results in very difficult to analyse situations in practice. For this reason, we need structured methodologies to analyse scheduling problems linked to specific circumstances.

To improve the understanding of scheduling problems, we believe a context-based analysis is useful. The context of scheduling problems can be interpreted in many ways. In this paper, we focus on two main parts of context; relating to the specific characteristics of the production process involved and relating to the tasks of the scheduler and others involved.

To some extent, the decision-making tasks have some generic aspects, although their relevance might be different in various situations. However, we submit that the configuration of characteristic elements of a production process are less generic and often strongly industry-specific and induce typical scheduling problems.

The aim of this paper is to develop an analysis methodology that combines insights from two research areas. First, the decision process of the schedulers, and secondly, the characteristics of the production process. So far, the combination of these two areas has been relatively ignored in the literature, especially concerning the food-processing industry. We aim to provide a conceptual contribution, grounded in empirical findings, that adds to the discussion on bridging the gap between scheduling theory and scheduling

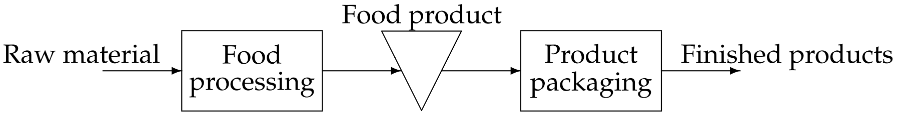

Figure 2.1. Typical two-stage food production process.

practice.

The paper is organised as follows. We first show the specific nature of food processing in section 2.2. Then, in section 2.3, we show that current approaches to scheduling fail to address the specific problems. Section 2.4 elaborates upon different ways to decompose scheduling problems: one based on the production process characteristics and one based on tasks. Section 2.5 then develops the context-based analysis methodology using and combining two decomposition methods. Finally, in section 2.6, our conclusions and some thoughts on further research topics are presented.

2.2 The food-processing industry

The food-processing industry can be considered as a part of the process industries, which is defined as 'firms that add value by mixing, separating, forming or chemical reactions' (Cox and Blackstone, 2002). In food processing, these operations are applied on agricultural raw material to obtain food products. The processing of this raw material can be continuous or in batches. When the latter is the case, one often refers to semi-process industries (Van Rijn and Schyns, 1993). In general, the production process can be divided into two stages: processing of raw materials into intermediate products and packaging of food products (see Figure 2.1).

A number of studies (*e.g.*, Meulenberg and Viaene, 1998; Nakhla, 1995) show the increasing need for flexibility, due to growing logistical demands as the result of the change in the market conditions for food-processing companies. Other changes are a tendency towards more diversity and the growth of unique products for certain customers, such as special offers (e.g., 10% extra, different packaging) along with specific orders for export. Certain products are demanded in limited quantities or with large gaps between orders. A quick response to changes necessitates proper scheduling and scheduling support (*e.g.*, Jakeman, 1994).

Problems in scheduling in the food-processing industry are specifically induced by the characteristics of the processes. The food-processing industry

Table 2.1. Case studies arranged by industry type.

Type	Industries	Number of characteristics Average	Range
1	Flour, Meat products, Grain processing	6.5	2–11
2	Pastry, Dairy (fromage frais), Ice cream, Snack food	4	1–7
3	Dairy (cheese, yogurt), Beer, Alimentary preserves, Freeze drying, Animal fodder	5.4	4–7
	Overall mean and range	5.2	1-11

Legend:
Type 1 — Raw materials are processed into intermediate products
Type 2 — Intermediate products are processed into end products
Type 3 — Raw materials are processed into end products

Derived from: Claassen and Van Beek (1993), Dov (1992), Fairfield and Kingsman (1993), Houghton and Portougal (1997), Jakeman (1994), Macchietto (1996), Moreno-Lizaranzu *et al.* (2001), Nakhla (1995), Randhawa *et al.* (1994), Roosma and Claassen (1996), Sivula (1990), Tadei *et al.* (1995), Van Donk (2001), Van Donk and Van Dam (1996), and 3 unpublished cases (flour, dairy, and pastry).

has a lot in common with other (semi-) process industries. Fransoo and Rutten (1994) and Van Rijn and Schyns (1993) describe typical characteristics for the (semi-) process industries.

Our compilation of food-processing characteristics is based on an analysis of case studies published in journals, conference proceedings, and books in the period from 1990 to 2001, complemented with the findings from recently conducted case studies by the authors. These studies involved factory tours and discussions with production managers and schedulers. The 17 cases are representative for the variety of the whole food-processing industry and are divided over all three types of processes distinguished in a report by Moret Ernst & Young Management Consultants (1997). Therefore, the sample satisfies the requirements of theoretical sampling (see Eisenhardt, 1989). Table 2.1 shows an overview of the case studies, as well as the average number of characteristics found.

Table 2.2 shows what characteristics are encountered in food-processing industry and how often they appear. We discuss shortly the effects of some characteristics on scheduling by taking two typical examples: setup times and perishability.

First, (sequence-dependent) setup times are often induced by numerous different tastes, colours, or concentrations (*e.g.*, Dov, 1992; Nakhla, 1995). The multitude of end products in the divergent product structure in most food-processing companies even aggravates the impact of setup time on scheduling. For example, Claassen and Van Beek (1993) describe a dairy company with about 2,500 end products, which are based on a few raw materials. In the production of such a wide variety of products, setup activities are frequently

Table 2.2. Compilation of product and production characteristics of the food-processing industry (including the number of times encountered in a case study).

Times encountered	**Characteristics**
$> 5 \times$	(Sequence dependent) set-up times
	Connectivity (no or limited intermediate storage allowed)
	Divergent product structure
	Perishable goods
	Shared resources
	Variable demand for end-products
$5 \times$	Limited capacity of machines and labor
	Variable yields/duration of process
$4 \times$	Varying position of customer order decoupling point
$3 \times$	Breakdowns cause disrupted schedules
	Only one line for job
	Production rate determined by capacity
	Scheduling by increasing flavor or color
	Variable time/quantity/price of delivery
$2 \times$	Combination of batch and continuous processes
	Production runs range from minutes to days
	Same operation, different productivity rates
$1 \times$	A lot of unit operations
	High quality demands
	Processing stage not labor intensive
	Ongoing innovation
	Partly homogeneous products
	Production of by-products

See Table 2.1 for sources.

encountered. A major problem in scheduling is to restrict the effect on capacity of these setups, while maintaining due-dates and inventory levels.

Secondly, perishability of (intermediate) products also has a significant impact on the production process; it has consequences for numerous production decisions like sequencing and stocking. Limited shelf life induces make-to-order production, which makes it harder to schedule production. Macchietto (1996) states that the perishability dictates segregation into batches and makes production scheduling more difficult. In food-processing companies, perishability is also a major topic concerning the high quality demands that have to be coped with. Another consequence of the perishability (of intermediate products) is that production stages often cannot be decoupled, and therefore have to be scheduled as one process (*e.g.*, Van Donk, 2001).

For most of the cases, several characteristics are present (see the average number in Table 2.1). As shown above, each of the characteristics in Table 2.2 induces its own scheduling problem. It mostly happens that several characteristics —and their corresponding scheduling problems— are present in a single case. As explained, dealing with sequence-dependent setup times can be complicated in itself. However, this will be even more complicated if several connected processes (with no or limited intermediate storage allowed) have sequence-dependent setup times. For instance, in dairy industries it can happen that the processing stage has to be sequenced from low to high concentrations of a certain additive, while in the packaging stage the preferred sequences are based on package size. Furthermore, sequence-dependent setup times are often accompanied with perishability, a divergent product structure, or connectivity. Interactions between these characteristics complicate the scheduling problem even more. Table 2.1 showed that, on average, a scheduler has about five characteristics to deal with. In one case, it were even eleven characteristics. This number of characteristics and their interactions are the reason for the complexity of scheduling in food processing. To some extent, we think that the type of characteristics and especially their combinations and interactions are typical for the food processing industry, but other industries will have other combinations of (probably also interacting) characteristics.

2.3 A review of scheduling approaches

In this section, we will first give some general observations and then discuss some specific applications that are of specific interest to the food-processing industry.

Scheduling is generally defined as the allocation of resources over time to perform a collection of tasks (Baker, 1974). It has been studied extensively, and numerous approaches to scheduling problems have been published over the last 50 years.

One of the main fields in scheduling research is operations research (OR). This resulted in a multitude of techniques, algorithms, and heuristics (see Kondili *et al.*, 1993; Morton and Pentico, 1993). Because of the advances in the computer sciences, these techniques have found their way to commercial software packages. However, the functionality provided in these packages is not always used (LaForge and Craighead, 2000). More than twenty years ago, Graves (1981) noted that the theory was not sufficiently developed to be applicable. This 'gap' between theory and practice still exists, according to McKay *et al.* (2002). However, in most cases, heuristic methods can find feasible solutions to scheduling problems, if they can be formulated mathematically. Finding an optimal solution normally requires a lot more time, which is not always possible. Nevertheless, the results in this area are powerful, but only if it is possible to work with structured, well-defined problems or if simplified scheduling problems can be constructed. The major problem is that quite a number of real-life problems cannot easily be formulated as a mathematical scheduling problem.

Another approach to scheduling is artificial intelligence (AI), which originates from the cognitive sciences. AI has its base in the work by Newell and Simon (1972). They view the scheduler's task as a cognitive process of understanding and recognising situations and the choices for appropriate measures. In this research area, the emphasis is on the observation and description of decision-making processes. It has influences from psychology and also researches other decision-making processes like playing chess (*e.g.*, Olson and Biolsi, 1991). Formalising and simulating these various decision-making processes caught much attention. Numerous methods were developed, such as constraint satisfaction, expert systems, and genetic algorithms (*e.g.*, Fox, 1990; Metaxiotis *et al.*, 2002; Kent and Steward, 2000). The original connection of AI with human cognitive processes has disappeared over time. Consequently, AI looks very similar to OR, and seems to suffer from the same 'gap' between theory and practice. Kempf *et al.* (1991) note that the use of scheduling systems developed in the field of AI is often not continued after the end of the research project. Moreover, according to Smith (1992), AI techniques are less useful in more complex scheduling problems.

Due to the lack of practical use of techniques from previously mentioned research areas, another area emerged in the field of cognitive sciences (CS), which returned to the original research approach of Newell and Simon (1972), where the focus is on the task of the scheduler (see also Ericsson and Simon, 1984). In these so-called task-oriented approaches, the main idea is that decision support must be based on the way the *scheduler* assigns the entities (machines, orders, operators, etc.), instead from mere assignment problems of entities. Decision support has to correspond to the different steps taken by the scheduler. Research in this area resulted in, for instance, the model for human scheduling by Sanderson (1991), the redesign of a scheduling task for decision support purposes (Wiers, 1997), the development of a scheduling framework based on the underlying structure of the scheduling task (Van Wezel *et al.*, 1996), and the development of a decision support system based on planning subtasks and data manipulation tasks (McKay and Wiers, 2003a).

Another good example of a task-oriented approach can be found in McKay *et al.* (1995). They describe the decision rules of a scheduler in a printed circuit board factory, using techniques like protocol analysis. The authors describe the decision process of the scheduler as neither official policy nor based on traditional methods of planning and scheduling. The scheduler uses information not normally used in analytical models, such as 'the attention of people from the third shift during the last training session'. The main question asked by McKay *et al.* is whether the scheduling decisions and the information they are based on can be included in software or algorithms. They conclude that part of the decision process could be encoded, but also that a significant part cannot be encoded using current methods. What appears to be 'common sense' to the scheduler is sometimes very hard to incorporate in models or algorithms.

A drawback of the task-oriented approaches is that its focus is on analyzing, modelling and supporting the existing scheduling tasks as performed by the scheduler, but less on adapting and improving the scheduling (Van Wezel and Jorna, 2001). Another interesting, much debated, but unresolved issue is what portion of the task is suitable for computerisation, and what should be left to human control (McKay *et al.*, 2002). As a consequence, the human factor in planning and scheduling is an upcoming and promising research topic (*e.g.*, MacCarthy and Wilson, 2001).

Several of the specific characteristics of the food processing industries are dealt with in the literature, for instance, random yields (*e.g.*, Yano and Lee, 1995), set-up times (*e.g.*, Vanderbeck, 1998), or perishability (*e.g.*, Gupta and Karimi, 2003). But as was stated in section 2.2, one often has to deal with several characteristics at the same time, which complicates the scheduling problem considerably. This has often been ignored in the literature. Variability in yields and uncertainty in processing times are other relevant characteristics that are relatively ignored.

To conclude, most OR and AI research focuses on simplified situations or simplified parts of the total scheduling problem and this results in techniques that are often not used in practice. Moreover, the OR/AI approaches mostly don't take into account the human aspect of scheduling. Research in the CS field focuses on the decision process and tasks of the scheduler, but little attention is paid to the characteristics of the production process to be scheduled.

So both approaches seem to be too generic to be valuable for improving real-life complex scheduling problems as those in food processing. We believe that scheduling methods should be based on both production system characteristics and the schedulers' task, and that this combination is the key to a successful approach to scheduling problems. In the next section we develop the building blocks for a combined approach.

2.4 Decomposition of scheduling problems

Decomposition is a common technique to deal with complex problems. Ovacik and Uzsoy (1997) state that decomposition methods attempt to develop solutions to complex problems by decomposing them into a number of smaller subproblems, which are more tractable and easier to understand (see also Simon, 1981). Ovacik and Uzsoy (1997) give two more arguments in favour of decomposition. First, not all parts of a problem are always equally important. By addressing subproblems in order of criticality, a solution of good quality can be found (see also Goldratt, 1986). Second, different operations to be scheduled can have different characteristics. This specific structure can often be used to gain computational advantages if used as a basis for decomposition methods.

After solving the individual subproblems, the solutions are integrated to form a solution for the initial problem. The combined solutions from the subproblems might not always be the same as a single solution for the whole problem. However, if the decomposition is performed carefully, the combined solutions can be a good approximation of the single solution, while being a lot easier to achieve. Bertrand *et al.* (1990) call this a decrease of decision freedom, which is countered by a reduction of complexity, which in turn improves the decision making.

Crawford *et al.* (1999) and Rolo and Cabrera (2000) state that the context is important in planning and scheduling. We state that this scheduling context can be understood in two ways; as the structure of the production process and as the decision process of the people involved in the creation of the schedule. The importance of product and production characteristics has been shown in section 2.2. The task-oriented approach emphasises that scheduling is not just an isolated decision-making task, but rather a number of connected tasks influenced by the organisation and its characteristics. This organizational context concerns elements such as the number of people involved in planning and scheduling and the use of information technology.

In the development of a context-based approach, we therefore use two different types of decomposition: a structural decomposition and a task decomposition.

2.4.1 Structural decomposition

In this paper, we interpret structural elements to be the characteristics of the production process, in terms of products, processing steps, storage possibilities, and transportation methods between stages. These elements can be used in the development of a structural decomposition. The inclusion of structural decompositions in our context-based approach to scheduling is based on the recognition that scheduling systems should better reflect realities of the plant (LaForge and Craighead, 2000). Therefore, one needs to have a thorough understanding of the structure of the production process and its specific characteristics.

Structural decomposition approaches

In the literature, several useful contributions to the structural approach can be found. The first two contributions we discuss are applicable in any industry type. The presence of industry-specific characteristics induces the need for specific tools to describe the situation. Therefore, the third and fourth contribution we present are especially useful in the food-processing industry.

First, an important concept in this field is the decoupling point, as introduced by Hoekstra and Romme (1992). This concept identifies the point in the production process where the production becomes order-driven. The production process is often scheduled in a different way before and after this decoupling point. Often, it is forecast-driven before the decoupling point and order-driven after the decoupling point. This results in different scheduling methods, but also different requirements on information flows and organizational responsibilities. Van Donk (2001) discusses a framework that adapts the decoupling point concept for use in the food-processing industry. Soman *et al.* (2004) also use this concept in the development of their hierarchical planning and scheduling framework for food processing.

A second contribution is the distinction between goods flow control and production unit control, introduced by Bertrand *et al.* (1990). A production unit is a part of the production system that over a short term is self-contained. It is responsible for the production of certain (intermediate) products from certain materials or components. Production unit control concerns the control activities with a local scope (within production units), such as sequencing rules. Goods flow control concerns control activities with a global scope; between production units and between production and sales. An example is the release of work orders to the production units. This approach focuses on the control structure, not on the application of mathematical techniques. This resulted from the strong belief that the design of production and inventory control systems requires a strong organizational viewpoint. In food processing, a production unit can be a single machine, but also a complete processing or packaging stage. The goods flow control becomes especially relevant in situations where batch processes and continuous processes are both present, which is quite common in food processing.

Third, we mention the process flow scheduling approach by Taylor and Bolander (1994), which is a constraint-oriented scheduling system, based on a thorough analysis of the production system. It uses a variety of concepts to define process structures. For instance, process trains is a concept that is used to denote a fixed sequential series of process stages in which a family of products is produced. The main principle behind process flow scheduling is that scheduling calculations are guided by the process structure (Taylor and Bolander, 1991). As this approach has been specifically designed for process industries, it obviously is attractive to use to analyse food processing. Next to structuring the production system, Taylor and Bolander also provide ideas on how scheduling could be performed, which again emphasizes the importance of a structural decomposition.

Finally, we present the capacity group concept and the process routing concept introduced by Van Donk and Van Dam (1996). A capacity group is defined by a number (sometimes one) of interdependent machines in one stage, which perform the same kind of (although not necessarily identical) operations. Process routings are fixed sequential series of operations in which a family of products is produced. These concepts were developed because the authors felt that concepts such as production units or process trains were not very attractive for many process industries and specifically for the food-processing industry. With the capacity group and process routing concepts, the structure of a specific scheduling situation can be analysed, based on typical characteristics as described in section 2.2, and scheduling problems can then be solved for each of the capacity groups.

Application

As production systems in food processing have a lot of connected equipment and shared resources, a thorough understanding of the structure is important. The approaches and concepts mentioned in this section, and summarized in Table 2.3, provide a certain view on scheduling, based on the process characteristics. The first two concepts provide a general structure, where the decoupling point has a customer-specificity viewpoint and the goods flow control and production unit control has a more hierarchical viewpoint. The last two concepts are especially applicable to food. Process flow scheduling provides tools to look at production systems in process industries and sug-

Table 2.3. Overview of the approaches and concepts suggested for the structural decomposition.

Focus	Concept	Main reference
Any industry:	• Decoupling point	Hoekstra and Romme (1992)
	• Goods flow control and production unit control	Bertrand *et al.* (1990)
Process industry:	• Process flow scheduling	Taylor and Bolander (1994)
	• Capacity groups and process routings	Van Donk and Van Dam (1996)

gest ways to organize the scheduling (*e.g.*, forward, backward). The process routing and capacity group concept focus on a more detailed level to gain a thorough understanding of the production system involved.

This set of approaches is used to decompose the production process to find relatively uncoupled parts and associated scheduling problems, which are easier to solve than the complete scheduling problem. Because scheduling problems are induced through the structure of the production process, decomposition of the production process gives the opportunity to decompose the scheduling problem. Combined with an analysis of specific characteristics encountered in a certain case (see section 2.2), the methods discussed in this section provide the means for the decomposition of the production process.

For example, structural decomposition often results in the grouping of resources. These groups of resources are in some way connected and have to be scheduled together. The connection between the resources can be physically (*e.g.*, through piping) or otherwise (*e.g.*, same operator needed).

In general, the characteristics of the food-processing industry presented in section 2.2 give a good indication of how to decompose the production system. For instance, the capacity group concept will group identical machines together. In scheduling, this might be used to first allocate a number of production tasks to the capacity group, while in a later stage the allocation and sequencing of the tasks can be performed.

As noted by Van Dam *et al.* (1998), a proper insight in the scheduling situation is essential for the design of a scheduling system. The structural decomposition methods described in this section aim to give this insight. In their paper, Van Dam *et al.* design a scheduling system for the packaging stage in a tobacco company. They also utilise concepts such as grouping to decompose the scheduling problem, which makes it easier to apply OR methods for several scheduling decisions.

2.4.2 Task decomposition

The cognitive process of the scheduler can also be used as a guideline for decomposition. The steps taken and activities performed by human schedulers to perform a scheduling task are identified and used as components in the decomposition. Here, the scheduling task is seen as the combination of actions and decisions of the scheduler to reach certain goals. In task decompositions one mostly speaks of subtasks instead of subproblems. Task analysis is performed to identify these subtasks.

Task decomposition approaches

In order to understand the scheduling process, a thorough task analysis is necessary. Therefore, research methodologies like field studies, action research, or even ethnographic studies (see *e.g.*, Crawford *et al.*, 1999; McKay and Wiers, 2003b) are necessary to obtain the necessary information. Within these methodologies, we identify three useful methods, that are mostly used simultaneously, to gather data.

First, observation can be a good method to acquire a basic understanding of which kind of tasks the scheduler actually performs. Here, tasks are identified on a relatively high level. Examples can be the collection of information or sequencing work for a certain capacity group. Also, the time needed to perform the individual tasks should be recorded. This is partly influenced by the observation that only a relatively small part of the scheduler's time (10–20%) is spent on the actual generation and modification of schedules (see *e.g.*, Crawford and Wiers, 2001).

Secondly, interviews are a logical next step. They can be used to get additional information on the observed tasks. For example, when it was observed that the scheduler discussed a certain element of the schedule with an operator, it is useful to know what goal the scheduler was trying to achieve. Was it just communicating the schedule, or was it an inquiry into the possibilities of relaxing certain constraints.

Finally, protocol analysis (see Ericsson and Simon, 1984) can be a useful tool to obtain further insights into the performed tasks. This is based on 'thinking aloud' sessions with the schedulers performing scheduling tasks. We believe it is especially useful for the actual schedule generation and modification tasks, as these tasks concern a high degree of problem-solving processes. This is also very interesting from a decision support viewpoint, as it is possible to divide the task into smaller subtasks that might be automated

Table 2.4. Examples of possible subtasks (non-exhaustive). Based on Higgins (2001), Van Wezel *et al.* (1996), and Wiers (1997).

Subtasks		
assigning jobs	monitoring performance	interpreting data
selecting jobs	estimating results	communicating schedules
ranking jobs	administrating production	investigating
counting jobs	evaluating actions	reacting to events

(see also Van Wezel *et al.*, 1996).

Application

The data gathered are analysed and used to decompose the activity of the scheduler. In the literature, we find several examples of task decompositions. For instance, Wiers (1997) performs a task analysis to identify and redesign subtasks to aid the design of a decision support tool. Van Wezel *et al.* (1996) develop a framework to facilitate the development of decision support systems, partially based on cognitive task analysis. They also state that a task decomposition will consist of two layers. First, subtasks have to be identified; secondly, the subtasks have to be specified. Higgins (2001) presents a production scheduling paradigm to address decision making in complex systems, which uses Rasmussen's (1986) cognitive work analysis. From these examples, we derived a (non-exhaustive) list of possible subtasks, which is presented in Table 2.4.

Task decomposition is also used in various AI-based methods, such as the constraint-directed scheduling method described by Smith *et al.* (1990). In this scheduling method, a framework is created consisting of various elements like knowledge sources and a scheduling maintenance system. It uses an opportunistic approach to guide the decision-making process, which is a commonly used approach (see also Hayes-Roth and Hayes-Roth, 1979). Based on this framework, a factory scheduling system is created.

Another important aspect in task decompositions is the fact that schedulers use 'enriched' data, which was demonstrated by McKay *et al.* (1995). For system developers, this kind of information is only available after a task analysis has been performed and gives useful insights in the scheduling process, although it may not be possible to 'computerise' this enriched data.

Considering the strength of human schedulers mentioned, the task decomposition of scheduling is promising. Research in this area has, until now, mostly stressed the importance of the human element, but combining computerisation and human control still seems to be a difficult topic (*e.g.*, Crawford *et al.*, 1999). Useful insights on this topic are provided by McKay *et al.* (1995), who studied the encodability of heuristics used by a scheduler.

2.5 Context-based analysis methodology

2.5.1 Description of the approach

In previous sections, both structural decompositions and task decompositions were explained. It was also stated that the structure of the production process and the task of the scheduler are the elements we understand to be the context of scheduling. Both decomposition approaches have promising results. A good understanding of the production process gives opportunities to improve the decision-making in scheduling, whereas the task approach helps in supporting the task execution and in clarifying the relations between tasks.

In the context-based approach we advocate, both the structural and the task decomposition are used to represent the scheduling situation. The structural elements provide insight into the product and production process characteristics, as discussed in section 2.2. Some of the elements can have a clear link to a mathematical approach. Elements from the cognitive side cannot always be analysed in this mathematical way, but they add knowledge and possibilities to the scheduling process and its organisation (see *e.g.*, McKay *et al.*, 1995). Combining structural with cognitive elements provides the opportunity to verify insights obtained in analysis of specific characteristics using insights from a task analysis of the schedulers' task. Also, a good knowledge of structural elements is necessary in understanding the scheduling task.

The framework we propose is presented in Figure 2.2. The structural and task decomposition are based on the concepts and methods presented in Section 2.4. For the structural decomposition, the first step is the determination of relevant characteristics (see section 2.2). Secondly, the identification of the structure, using concepts like process routings, process trains, goods flow control and the decoupling point. After the identification of the structure, a specification can be made, using concepts such as capacity groups and production units. A similar three-step approach is used for the task decomposition. First, the scheduling task has to be determined. Secondly, scheduling subtasks are identified using *e.g.* observation and interviews. Thirdly, a more thorough study based on thinking aloud and protocol analysis is performed to specify the subtasks.

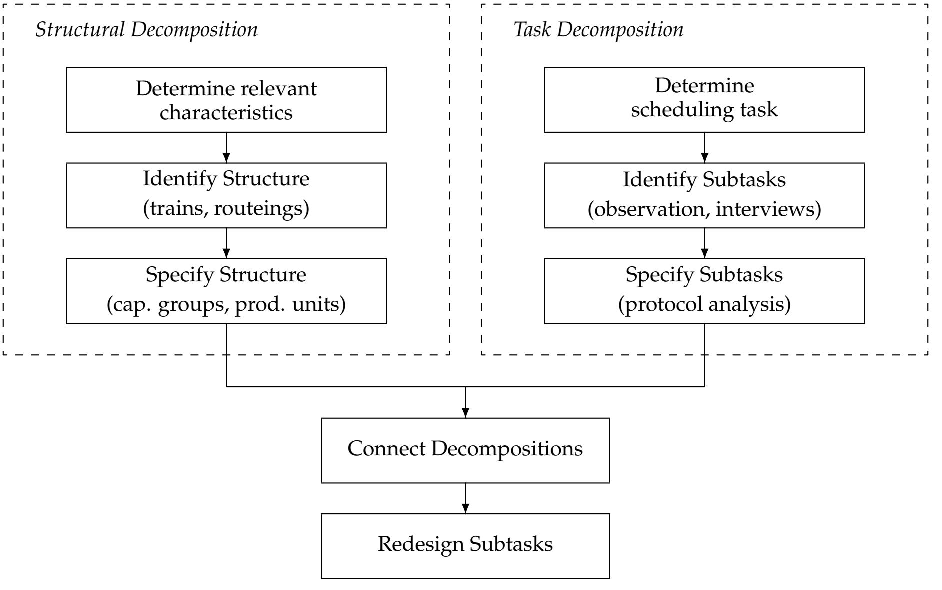

Figure 2.2. Schematic representation of the context-based approach to analyse scheduling problems.

The specific applicability to the food-processing industry is found in the choice for methods to perform the structural decomposition. In section 2.2, several characteristics were identified as common for the food-processing industry. The presence of these characteristics makes certain decomposition methods more useful than others. For instance, the capacity group concept is very useful in environments where we see the use of shared resources and in situations where the same operations can be performed with different productivity rates. A concept like process trains would be less useful in this case, as it quickly encompasses whole production systems in food processing (where a lot of the equipment is shared or connected).

Concerning the connection of the decompositions, it is possible to specify relations between the scheduling subtasks and elements from the structural decomposition. It is unlikely that this will result in a collection of one-to-one relations. The final network of relations will probably consist of one-to-one, one-to-many, and many-to-many relations (as illustrated in Figure 2.3).

A related issue is the connection between tasks. Not all tasks need to be directly sequential or have a fixed order. However, tasks that would be identified in a holistic sense often have several, more visible, occurrences that do have their place in a sequence. For instance, the gathering of information could be seen as a holistic activity, which becomes more visible in combina-

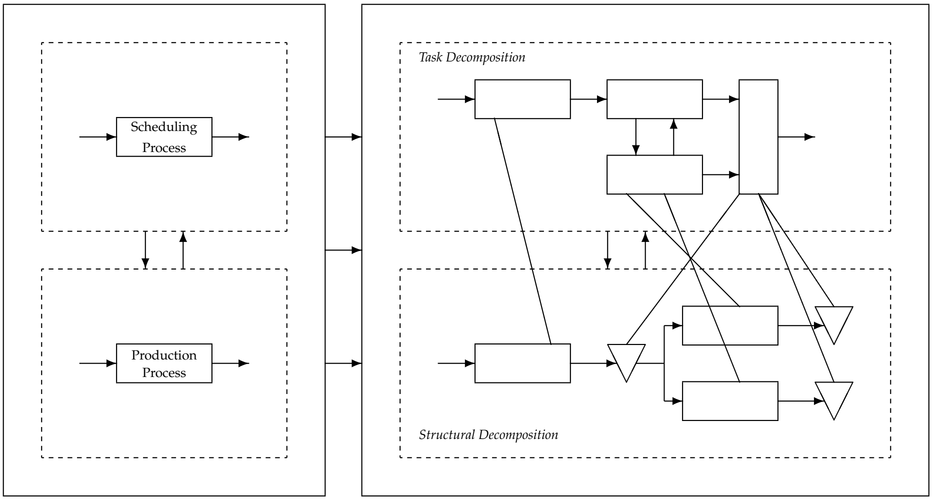

Figure 2.3. Decomposition in the context-based approach.

tion with subtasks that use specific information.

If independent subnetworks (sets of subtasks) arise from the decomposition, these can be evaluated in the light of possible computerisation (see also McKay *et al.*, 1995). For each individual subnetwork, it can be decided whether or not it is suitable for computerisation. However, there are also possibilities between no computerisation and full computerisation. In some cases, the solution may be between these extremes. For instance, in a sequencing task for a certain capacity group, the computer could generate possible scenarios, from which the scheduler can pick the most attractive sequence. Note that this does not necessarily have to be the sequence that the computer would think to be optimal.

The resulting framework has three important potential results. First, the identification of independent sets of subtasks, which can possibly be (partly) supported by scheduling algorithms or heuristics. In addition, the relations between the scheduling tasks, as well as the relations between scheduling tasks and production structure, are clarified. This provides two additional outcomes: it can be helpful in evaluating the organisational structure; and it reveals the information structure wherein scheduling is embedded.

Because of the first result, the framework can also make use of the enormous amount of scheduling research in the OR and AI communities. Some subtasks could be computerized or supported by heuristic or algorithmic approaches, while other subtasks could remain with the scheduler. We believe that this could improve the practical use of decision support systems, because the resulting system would have its basis in the elements from the scheduling task.

2.5.2 Illustrative example

To illustrate our framework, we present a small example from a meat products company. In this example, task analysis resulted, among others, in numerous rules-of-thumb used by the scheduler. In the scheduling of a certain capacity group, one of the rules used to assign capacity was that two particular packaging lines were never to be used at the same time. Initially, it was unclear why this rule was used. Based on structural analysis, the underlying reasoning turned out to be that a sterilisation process, situated just after these packaging lines (in the same process routing), could only process the output of one line at once. This reason became clear after evaluating what food-specific characteristics were present in the company. The characteristics 'connectivity', 'shared resources', and 'production rate determined by capacity' describe the situation. Figure 2.4 presents the relevant parts of the structural and task decomposition.

This example also illustrates the three potential outcomes mentioned in the previous section. First, regarding the use of algorithms to support subtasks, it is clear that 'sequencing packaging' could be mathematically solved. Secondly, the organisational structure can be evaluated on the basis of the network of subtasks. For each of the subtasks, responsible parties can be identified. These could also be reallocated. For example, in this small example, it wouldn't make sense if the subtasks were divided among several people. The person who assigns the capacity and sequences the packaging lines should also be able to negotiate the schedule, as he or she knows the underlying objectives. Finally, the information structure is revealed. The information for assignment of products to the packaging lines is required on a higher level (*i.e.* capacity group) than the packaging line information needed to sequence the packaging lines.

2.6 Conclusions

In this paper, the scheduling situation in the food-processing industry is studied, and a context-based analysis methodology for scheduling problems is proposed. The emphasis of this study is on the context of scheduling, in which we make a distinction between the structural and the task context.

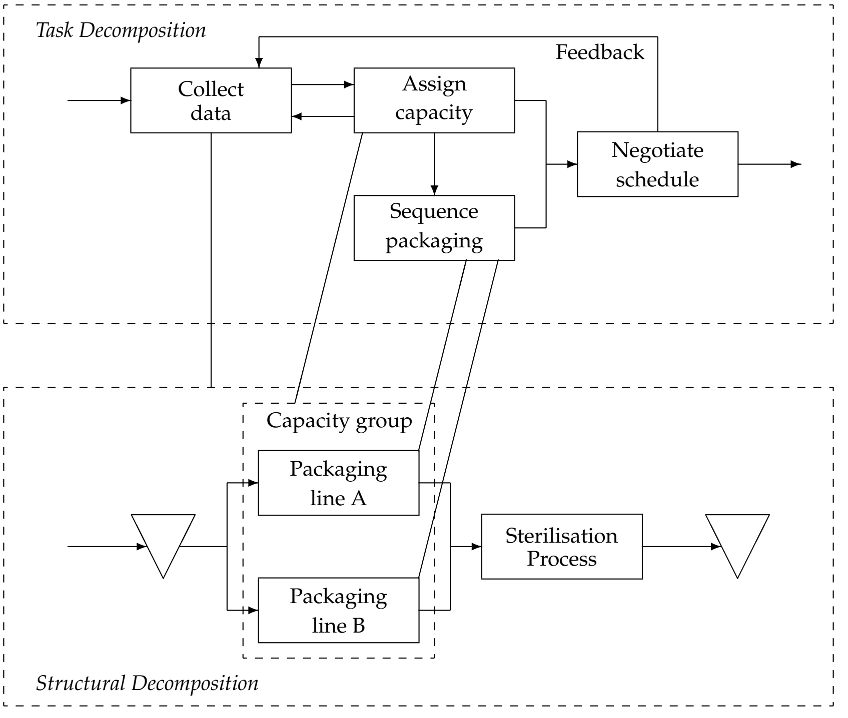

Figure 2.4. Schematic representation of a part of the structural and task decomposition in the example of the context-based approach.

The structural context is the structure of the production process, especially focused on product and production characteristics; the task context is the cognitive decision-making task of the scheduler. In previous research, the structural insights have hardly been studied and a combination between structural and cognitive approaches has also had little attention.

To develop a context-based view on scheduling problems in the food-processing industry, we first reviewed the industry-specific characteristics. This overview of characteristics gives a reasonable representation of the industry and shows the complexity of its scheduling problems. Secondly, a number of research areas are discussed to review their capabilities to deal with the complexity of the scheduling situation. Thirdly, we discussed structural decompositions and task decompositions, which are combined into our context-based approach in the final part of the paper.

Our combination of structural and cognitive insights can be positioned in one of the six high-impact research issues recently identified by McKay *et al.* (2002). They mention 'task design' as one of these research issues, and this concerns, among others, the cooperation between the scheduler and the support system. This support system is often based on decomposition, which is very important for its usability. The cooperation could benefit from using structural and cognitive insights in the decomposition process. With this study, we add to the ongoing discussion to bridge the gap between theory and practice in scheduling research.

Application of the context-based approach in real-life food-processing companies gives a good insight in the scheduling problems. Furthermore, it seems possible to make better use of the existing body of knowledge within the world of scheduling research, and to evaluate the organization and information structure around the scheduling problems.

We realise that our context-based approach also has limitations. More is needed to apply it in different situations and to better relate it to the characteristics of food processing. We also acknowledge the importance of the user of the methodology. After a fairly generic way of identifying a structural and a task decomposition, the analysis part might be more subjective. The user still has to evaluate the resulting decompositions, and judge the possibilities for computerisation and the organisational aspects. However, with our approach, we believe that a thorough study of the structural and cognitive elements is a significant step in this process.

Topics for further research can be found in the use of OR and AI techniques for the construction of decision support for subproblems in the decomposition. In this paper, a conceptual contribution is presented. The application in real-life settings is needed to test the context-based approach in practical scheduling situations.

The method proposed in this paper is designed for the food-processing industry. The industry-specific character lies mostly in the choice for methods in the structural decomposition. We think the approach could also be used in other types of industry, if the choice for methods to be used in the structural decomposition is suitable for the specific industry. For instance, due to the high degree of connectivity between equipment found in food processing, we use concepts like process routing to analyse the dependence between the scheduling decisions. For discrete industries, workstations often operate more independently. Therefore, process routings may probably have other effects.

CHAPTER 3

Capacity and Time Constraints

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RENZO AKKERMAN, DIRK PIETER VAN DONK, AND GERARD GAALMAN (2006), *The influence of capacity- and time-constrained intermediate storage in two-stage food production systems*, International Journal of Production Research, accepted for publication.[1]

Abstract

In food processing, two-stage production systems with a batch processor in the first stage and packaging lines in the second stage are common and mostly separated by capacity- and time-constrained intermediate storage. This combination of constraints is common in practice, but literature hardly pays attention to this. In this paper, we show how various capacity and time constraints influence the performance of a specific two-stage system. We study the effects of several basic scheduling and sequencing rules in the presence of these constraints in order to learn the characteristics of systems like this. Contrary to the common sense in operations management, the LPT rule is able to maximize the total production volume per day. Furthermore, we show that adding one tank has considerable effects. Finally, we conclude that the optimal setup frequency for batches in the first stage is dictated by the storage time constraint.

3.1 Introduction

In the food-processing industry, production systems often consist of two stages. In general, the first stage concerns the batch processing of raw material into food products, which are packaged in the second stage.

[1] An earlier version of this paper was published as: RENZO AKKERMAN, DIRK PIETER VAN DONK, AND GERARD GAALMAN (2004), *Storage between two production stages: Scheduling with capacity and time constraints*, in Pre-prints of the Thirteenth International Working Seminar on Production Economics, February 16–20, 2004, Igls/Innsbruck, Austria, Volume 1, pp. 19–34.

In previous research (*e.g.*, Van Donk, 2001), perishable goods, shared resources (such as tanks), and a divergent product structure were identified — among others— as important characteristics of food processing. These characteristics imply the presence of two types of intermediate storage limitations: capacity constraints and time constraints.

The capacity constraints are present because of a limited number of storage tanks, which often have to be shared by a multitude of products. Of course, each of these tanks also has its own capacity constraint (its maximum content). Furthermore, batches can not be stored concurrently, due to quality and traceability requirements. These constraints become even more relevant if the number of products is greater than the number of tanks, or if not all products can be stored in every tank.

The second storage limitation, time, is present due to the perishability of the intermediate food product. Unpackaged intermediate products are often more perishable than packaged products, which makes the storage time constraint in the intermediate stage of the production process more important than in other stages (raw material, final products). Within a certain time period, the product has to be packaged and transported to the customer, or else the product has to be disposed of as waste or low-quality by-product.

There are many practical situations where the two types of storage constraints are encountered. For example, in the production of dairy products, the customer often demands a certain best-before date. Thus, the possible storage time of perishable intermediates in the production process is very short. Another example is the production of flour, where intermediates have to be stored in a limited amount of silos. Due to different grains and different mixtures, the number of intermediates is very large, which can result in blocking effects caused by tank unavailability.

In the literature (discussed in section 3.2), intermediate storage is often considered as one single capacity constraint and the time constraint is hardly covered. This paper studies production systems with both types of constraints. We study the performance of a specific two-stage system under these constraints, and use several well-known (common-sense) heuristic sequencing approaches. For this study, we aim to explore the impact of the intermediate storage constraints. We believe a better understanding of the implications of these storage constraints is necessary as a starting point for the design of solution procedures for scheduling problems. We emphasize that in this paper, it is not the aim to develop a specific mathematical model and solve this to optimality. Instead, we consider this an exploratory study using a relatively simple stylized production system (but representing all (real-life) complexities in terms of interactions between production capacities and intermediate storage). We use simulation to investigate the behaviour under various capacity and time constraints on intermediate storage. We focus on several performance measures such as flow time, makespan, and waste. Underlying these measures, blocking and starvation effects play an important role. In the experiments, we also study the effect of uncertainty in processing times —as this is expected to influence blocking and starvation effects.

The paper is organised as follows. First, we discuss previous results on two-stage production systems. Then we outline the production system we study in this paper and several heuristic scheduling approaches to be used in scheduling this production system. Subsequently, we present the results of simulation studies, which is the main contribution of this paper. Finally, the last sections will contain a discussion of the results and suggestions for further research.

3.2 Literature background

There is a significant amount of studies that concern two-stage production systems. These systems already offer considerable complexity, as demonstrated by Gupta (1988). Johnson (1954) was one of the first to study such a system, with one machine in each stage. More recently, most papers address systems with one machine in the first stage and multiple machines in the second stage (*e.g.*, Gupta and Tunc, 1991; Tsubone *et al.*, 1996; Li, 1997). This type of problem is often found in process industries (Narasimhan and Panwalkar, 1984), and it resembles the typical divergent structure of production processes found in the food-processing industry (Akkerman and Van Donk, 2006a).

A lot of studies, however, do not consider limited intermediate storage possibilities between the production stages. In the food-processing industries, we can distinguish capacity and time constraints on intermediate storage. Capacity constraints have been considered in several publications. In most cases, the limitation is included as an overall capacity constraint (*e.g.*, Papadimitriou and Kanellakis, 1980; Nowicki, 1999), but several papers incorporate storage in the form of tanks (*e.g.*, Belarbi and Hindi, 1992; Yi *et al.*, 2000). From these papers, we learn that complex scheduling problems arise, which often can only be solved heuristically. We also see that tank availability is a specific concern in such situations and a main element in the modeling.

Time constraints also received some attention in previous research, but relatively few studies consider this constraint (*e.g.*, Yang and Chern, 1995; Su, 2003). Here we see that the time constraint dominates the development of heuristics and tighter constraints require more calculation efforts. To the best of our knowledge, the specific combination of capacity and time constraints has not been addressed in the literature. Furthermore, the complexity of the scheduling problems and the inherent difficulties in developing solution methods leads us to believe a good insight in this combination of constraints is important.

In our study, the first stage concerns a batch process. In the literature, the concept of batching is used in different ways. First, due to efficiency reasons, it can be convenient to process several jobs in a batch instead of processing them individually (see *e.g.*, Potts and Kovalyov, 2000). For example, setup times can be involved when switching between product families. Then, the batching is the result of scheduling reasons and is called family scheduling (Webster and Baker, 1995). The main issue in family scheduling is the tradeoff between minimal setup times and the order delivery time. Large batches delay the processing of orders from other product families (Potts and Kovalyov, 2000). Secondly, batching can also have technical reasons. In process industries, the processing stage often concerns non-discrete products, and processing technology often implies the need for batching. Then, a batch can be defined as a quantity that is planned to be produced in a given time period based on a formula or recipe that often is developed to produce a given number of end items (Cox and Blackstone, 2002). The batch sizes usually depend on the capacity of the batch processor. This is identified as batch processing (Webster and Baker, 1995).

In the above terminology, the kettle process in this paper is a batch processing machine. However, in our case, the sequencing of kettles is another relevant issue, because we assume setup times between product families. Therefore, scheduling the kettle process in this paper includes elements from batch processing *and* family scheduling. Furthermore, the intermediate storage time limitations we include also influence the coordination of the scheduling of the kettle process (see also Silver, 1989). In the field of chemical engineering, we also find various approaches to the scheduling of batch processing operations, mostly based on mixed integer linear programming (MILP) techniques (see *e.g.*, Kondili *et al.*, 1993; Pinto and Grossmann, 1998). Although these papers provide sophisticated production scheduling procedures, these approaches do not provide a thorough insight in the effects of

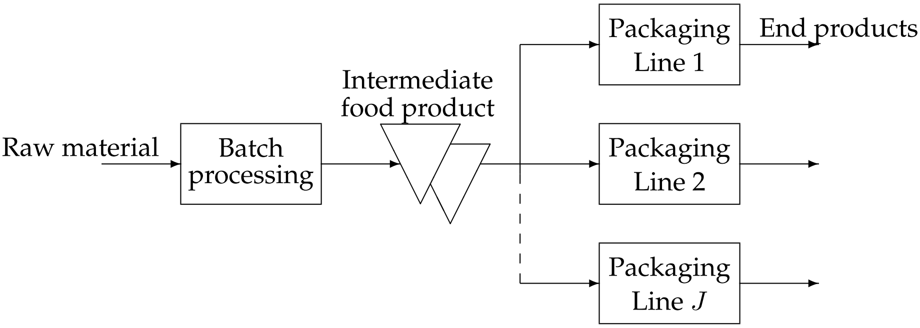


Figure 3.1. General form of the two-stage production process with a batch processor in the first stage and J parallel packaging lines in the second stage.

constrained intermediate storage.

3.3 Problem formulation

3.3.1 Production system

Figure 3.1 illustrates the production process studied in this paper. It is based on experiences in the food-processing industry, where such two-stage processing and packaging systems are very common. Although it is a relatively simple system, it contains all basic elements that determine the complexity of two-stage food production. In this way, we think that the results of the study provide general insights into the interactions and characteristics found in two-stage systems with intermediate storage in the food-processing industry.

The first stage consists of a kettle process, where J different intermediate products are produced. The kettle content B is fixed and it requires a processing time $p_{1,j}$ to produce one kettle of intermediate product j. This processing time is subject to uncertainty, due to variation in the quality of the raw material. In the food-processing industry, the raw material usually originates from the agricultural sector. These materials often have a variable quality by nature. During the processing time, the product stays in the kettle, and can only be transported to a storage tank after processing ends.

If multiple kettles of one product are produced in one batch, no setup time is required between these kettles. However, when changing to another product, a — sequence-independent — setup period S_{up} is necessary. In this paper, a number of consecutively produced kettles of one product is referred to as a batch.

There are K storage tanks, which can each hold M finished kettles of an intermediate product. Two types of constraints are present for the intermediate storage: (i) a capacity constraint, concerning the number of tanks and their maximum content, and (ii) a storage time constraint. The capacity constraint is influenced by the fact that it is not allowed to store product from kettles in different batches in one storage tank, due to traceability issues. Due to this separation of batches, it is more likely that intermediate storage tanks are unavailable for a new batch.

The storage time constraint is related to the customer's requirements concerning the best-before date of a final product. To ensure a long best-before date, the intermediate product that is used for an end product has to be packaged within a maximum time $T_{\max}$. If several kettles of a product are stored in the tank, the finishing time of the first kettle determines the maximum storage time.

In the second stage of the production system, J packaging lines are available to create various end products from each of the J intermediate products. The unit processing time $p_{2,j}$ varies due to differences in packaging sizes. For small packaging sizes, it takes more time to package a certain amount of product, than for larger packaging sizes.

Finally, for reasons of simplicity, we make the following assumptions:

- The transport times between the batch processor and the storage tanks are negligible.
- Withdrawing product from tanks for packaging can only begin after batches are finished.
- Every storage tank can be used to store every intermediate product.
- Raw materials and packaging materials are always available.
- Storage of finished products is not relevant, as all products are immediately shipped to the customer.
- The production system operates only on weekdays, for eight hours per day.

3.3.2 Product flow and scheduling

Customer orders for the end products arrive during working days, and have to be delivered the next day. The number of orders O_j for each product family

j varies from day to day. All orders also have their own packaging format requirements, which will be relevant in scheduling the packaging stage. At the start of each day, all orders become available to the planning department. At this time, schedules for the first and second stage can be created based on the orders and the current intermediate storage levels. However, this is not the only moment scheduling decisions are made. When the kettle process in the first stage has finished producing the intermediates that are needed to package the set of orders for the current day, it can be considered to make intermediate product for the next day. This is based on whether there is time left on the day and whether intermediate storage space is available.

In the first stage, a cyclic scheduling approach is adopted. According to Pinedo (2002), this is often the case in flow lines with limited intermediate storage. The approach is also attractive, because it will periodically supply different intermediate products to the second part of the production system, providing inputs for the packaging stage. The setup frequency for each intermediate product is denoted by the design parameter S_f, which is equal to the amount of cycles per day.

In each cycle, every product is produced once. The amount of kettles in a batch depends on the amount of products requested by the customer and the usable amount of product in the intermediate storage (where the usability is derived from the time constraint). We use L_j to denote the amount of kettles of product j that are needed on a certain day. This amount can be calculated by[2] $L_j = \lceil (O_j - U_j)/B \rceil$, where B is the kettle content, U_j is the usable amount of product j which is in the intermediate storage at the start of the day, and O_j the amount of products from family j to be produced that day — collected on the day before. Finally, these L_j kettles are divided between the production cycles. That means that the p^{th} cycle for product j (called CL_{jp}) has $\lceil (L_j - \sum_{i=1}^{p-1} CL_{ji})/(S_f - (p-1)) \rceil$ kettles.

For the additional production at the end of the day, this cyclic scheduling approach will be continued. However, the batch size (in kettles) cannot be based on customer demand, because this information is not available until the next day. Therefore, it is based on a forecast of the requested orders for the next day. On Fridays, no additional production is scheduled, because due to the storage time constraint, the product would be unusable on the next Monday. As compensation, the kettle process is started earlier on Mondays. For the remaining weekdays, production at the end of the previous day can

[2] The notation $\lceil x \rceil$ is defined as the smallest integer greater then or equal to the value of x, or mathematically speaking: $\lceil x \rceil = \min\{y \mid y \in \mathbf{N}, y \geq x\}$.

be used and starting earlier is not necessary. In this way, the production is mostly done during the regular working hours, which can be economically attractive.

In the second stage, the intermediate product is packaged to satisfy the customer orders. Because of the varying packaging times, the packaging sequence influences the speed at which product is extracted from the tanks. In this paper, we use three different ways to sequence the production in this stage:

- FCFS rule (First Come, First Serve), where the orders are processed in the order they arrive. The main idea behind the inclusion of this rule is its usefulness as a benchmark. In many cases it is also attractive because it results in a low variance of flow time (see *e.g.*, Rajendran and Holthaus, 1999).

- SPT rule (Shortest Processing Time), which arranges the products according to an ascending order of unit processing times. This rule is traditionally seen as the best rule in terms of flow time (see *e.g.*, Holthaus and Rajendran, 2002), although some authors discuss its effectiveness in situations with bottlenecks (see Bassett and Todd, 1994).

- LPT rule (Longest Processing Time), which arranges the products according to a descending order of unit processing times. According to Tsubone *et al.* (1996), this rule yields good results in terms of the maximum work-in-process level, which makes it especially interesting to consider in a situation where storage is constrained (in capacity and time).

The storage constraints are an important characteristic of this production system. Both the production cycle in the first stage and the packaging sequence in the second stage interact with these constraints. This interaction results in blocking and starvation effects. Blocking occurs when the kettle process finishes, but there is no intermediate storage tank available. This means the product stays in the kettle until a tank becomes available and therefore temporarily blocks further production. The blocking effects are strengthened by the traceability requirements mentioned before. Even a small amount of the same product as in the kettle could block a storage tank. Starvation occurs when there are customer orders to package, but the required intermediate product is unavailable. Then, the packaging line is idle until the intermediate product becomes available.

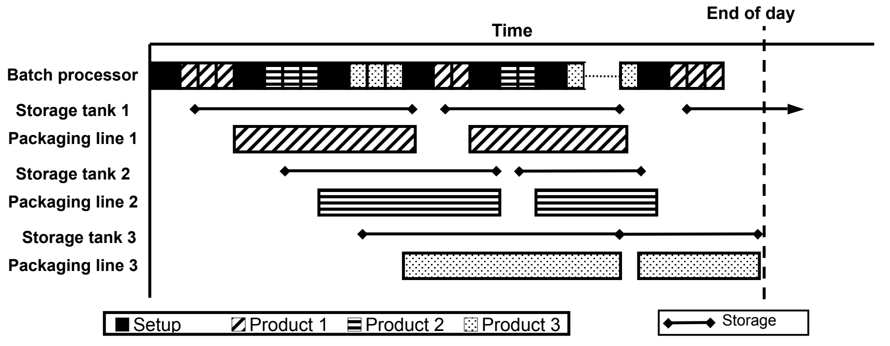


Figure 3.2. Schedule for the example case.

If there is much blocking and starvation, it can be the case that it is not possible to satisfy all customer orders within the time available.

3.3.3 Illustrative example

To clarify the characteristics of the production system, figure 3.2 shows an example of a production schedule for a system with three packaging lines, three storage tanks with a content of three kettles ($J = 3$, $K = 3$, $M = 3$). In this example, we present a situation where two production cycles are processed in the first stage ($S_f = 2$) and the intermediate storage tanks are empty at the start of the day. The storage time constraint is assumed to be nonrestrictive. The impact of the capacity constraint is visible through blocking and starvation effects. For each of the product families, five kettles of intermediate product are needed to satisfy demand ($L_j = 5, \forall j$).

Starvation is seen at the start of the day, and during the day after the packaging of the first batches. Blocking effects can be seen in the first stage. After the production of the first kettle in the second batch of product 3, there is no storage tank available. Only after a tank becomes available, the content of the kettle can be moved to this storage tank.

This example also provides insight into the effect of production in advance. At the end of the day, there is sufficient time to start with a new production cycle. However, there is a reasonable chance that blocking effects will occur, due to the situation that no storage tank is available. In the example, one additional batch of product 1 is produced to create a starting inventory for the next day. If this is possible (considering capacity and time constraints), there is a significant time advantage on the next day. This advantage is that one of the packaging lines does not have to wait until the batch processor finishes the first batch, which reduces the amount of starvation.

3.3.4 Performance criteria

For the formulation of the performance criteria, we introduce several additional variables. For the first stage, let $S_{1,jl}$ and $C_{1,jl}$ be the starting time and completion time for the l^{th} kettle process of intermediate product j (from a total of L_j kettles). For the second stage, we define $S_{2,jo}$ and $C_{2,jo}$ to be the starting time and completion time for the packaging of the o^{th} order an end product from family j. As defined earlier, we use O_j to denote the number of orders for product j (for the current day).

First, we will use daily flow time, makespan, and the amount of unfinished orders to evaluate the production systems ability to finish the requested orders. With the flow time, we have a indication of the time the orders spend in the production process, which (for practical considerations) translates into lead times for individual orders. The makespan gives us an idea on the total time needed to finish the daily production. We denote these criteria by FT, MS, and UF and calculate them as follows:

$$FT = \sum_{j=1}^{J} \sum_{o=1}^{O_j} C_{2,jo}, \tag{3.1}$$

$$MS = \max_{j,o} C_{2,jo}, \tag{3.2}$$

$$UF = \sum_{j=1}^{J} \sum_{o=1}^{O_j} I^u_{jo}, \tag{3.3}$$

where I^u_{jo} is an indicator function, defined as follows:

$$I^u_{jo} = \begin{cases} 1, & \text{if the } o^{\text{th}} \text{ order for a product from family } j \text{ is unfinished} \\ & \text{at the end of the day} \\ 0, & \text{otherwise.} \end{cases}$$

Due to the limited storage capacity, we also measure the amount of blocking in the first stage and the amount of starvation in the second stage to evaluate the systems performance. These criteria will provide insight on the effects of the limited number of storage tanks between the two stages. In this formulation, we let $T_{1,jl}$ denote the moment in time that the l^{th} kettle for family j is transported to an intermediate storage tank. The amount of blocking is then calculated in the following way:

$$BL = \sum_{j=1}^{J} \sum_{l=1}^{L_j} (T_{1,jl} - C_{1,jl}), \tag{3.4}$$

and the amount of starvation as follows:

$$ST = \sum_{j=1}^{J} \Big(\sum_{o=2}^{O_j} (S_{2,jo} - C_{2,j(o-1)}) + S_{2,j1} \Big). \tag{3.5}$$

The other additional element in this paper is the limited waiting time of products in the intermediate storage. Therefore, it can happen that a batch of intermediate product becomes obsolete and unusable for further production. The last performance criterion we include is therefore the amount of waste. Here, SL_k and FD_k denote the storage level of product in tank k and the fill date of tank k. We measure the time constraint on intermediate storage in days, so the waste on a certain day d can be calculated as follows:

$$WA = \sum_{k=1}^{K} I_k^w SL_k, \tag{3.6}$$

where I_k^w is defined as follows:

$$I_k^w = \begin{cases} 1, & \text{if } d - FD_k > T_{\max} \\ 0, & \text{otherwise.} \end{cases}$$

3.4 Numerical experiments

Several experiments have been performed to analyse the performance of various configurations of the production system. The aim of these experiments is to study the influence of several intermediate storage constraints, and to study the applicability of different sequencing rules in the packaging stage.

As was mentioned in Section 3.3, there are several elements subject to uncertainty. In the simulation study, these are inserted as follows. The batch processing time $p_{1,j}$ is generated from a truncated normal distribution with average $\bar{a}$ and coefficient of variance cv_a.

The customer orders for products from family j arrive during the day following a Poisson distribution with an average of λ units per day. For the second stage, the unit processing time $p_{2,j}$ is dependent on the packaging requirements of the customer and is randomly set at $b_{\min}$ or $b_{\max}$, where $b_{\min} = \bar{b} - b_{\text{dev}}$ and $b_{\max} = \bar{b} + b_{\text{dev}}$. With this implementation, we are also able to study the effect of smaller and larger differences in packaging times by varying b_{dev}.

We expect that the uncertainty in the processing times has a significant impact on the performance of the production system. Variation in the moment that products are transported to the intermediate storage tanks and the

Table 3.1. Initial values of parameters used in the model.

Parameter	Value	Parameter	Value	Parameter	Value
λ	50 units/day	K	3 tanks	$\bar{a}$	15 minutes
J	3 families	M	5 kettles	cv_a	0.2
S_{up}	25 minutes	B	10 units	$\bar{b}$	5 minutes
S_f	2 cycles	$T_{\max}$	1 day	b_{dev}	1

moments that they are extracted from these tanks influences blocking and starvation effects and will therefore affect the systems performance.

Next to the effect of uncertainty, we will also study various configurations of the intermediate storage system. We will study capacity-constrained intermediate storage by looking at different numbers of storage tanks, as we are interested to see to what extent there is an effect on the performance criteria through increased or decreased blocking and starvation.

Finally, we also look at time constraints for the intermediate storage. We expect tight storage time constraints to have a big influence on the performance of the sequencing heuristics and also the choice for a specific setup frequency.

The parameter settings used in the initial model are listed in table 3.1. The simulation results in the following section have all been derived from 100 simulation runs of 10 weeks. It should be noted that, due to the storage time constraint, the products in the intermediate storage cannot be stored over the weekend. This results in independence between weeks. Therefore, the run length in weeks is arbitrary, as long as it is a number of full weeks.

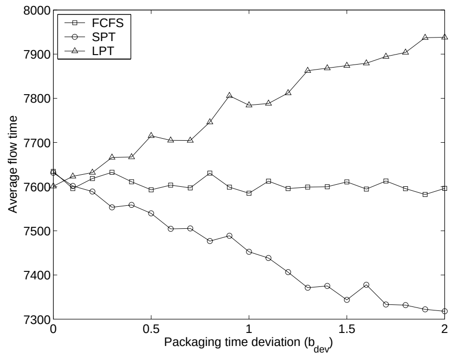
3.5 Simulation results

3.5.1 Effects of uncertainty

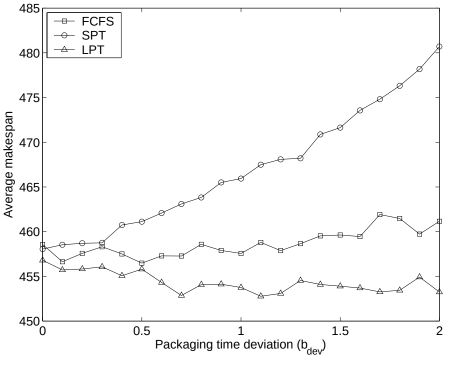
To evaluate the effect of the sequencing rules used in the second stage, we will first look at various differences between the processing times by varying b_{dev}. Greater variation in these processing times should increase the effects of using a certain sequencing rule. All other parameters have the values listed in table 3.1.

In figure 3.3, the flow time and makespan are shown for various values of b_{dev} and various sequencing rules. The value of b_{dev} represents the variation in packaging times.

As can be seen in these figures, the amount of variation in the packaging time in the second stage has significant effects on the flow time and the



(a) Average flow time

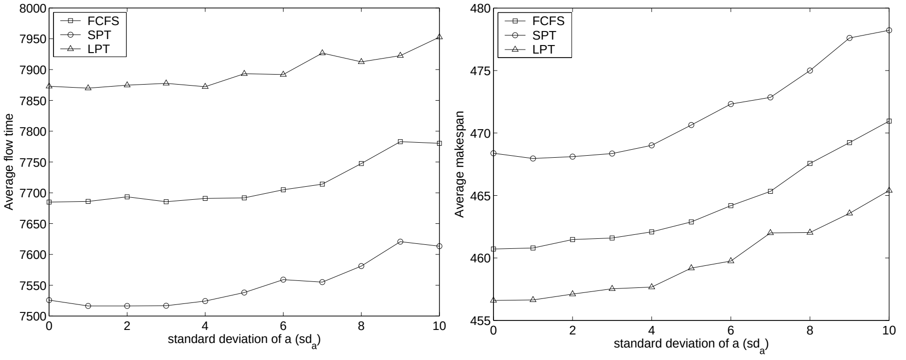


(b) Average makespan

Figure 3.3. Average flow time and average makespan against b_{dev} for various heuristics.

makespan. First, using certain sequencing rules becomes more important. The result from figure 3.3(a) can be explained by the definition of flow time (summation of finishing times). If all orders with small processing times are processed first, it is obvious that a sum of completion times is smaller then if orders with long processing times are processed first. However, despite the disadvantage in flow time, the makespan is lower for the LPT sequencing rule (as shown in figure 3.3(b)). This is due to an increase in the amount of starvation time; because when the second stage finishes packaging relatively soon (SPT rule), it has to wait for new intermediates to continue. The amount of blocking time is relatively constant, due to the fact that this also occurs before or during the additional production. However, this part of the blocking time does not affect the packaging of customer orders.

Next, the effect of uncertainty in the batch processing time is studied. With more uncertainty, we expect that the chances of blocking and starvation increase, which in turn could effect our main performance criteria, like flow time and makespan. Therefore, in figure 3.4, the flow time and makespan is shown for various values of sd_a, which is the standard deviation of $\bar{a}$. More variation in the batch processing time increases the flowtime and the makespan of the production system. This can be explained as follows. If the variation in the batch processing time increases, we both get batches that take a longer time and batches that finish faster. In the first case, makespan and flow time are negatively influenced. In the second case, this does not necessarily have to be true. It is possible that no intermediate storage capacity is



(a) Average flow time

(b) Average makespan

Figure 3.4. Average flow time and average makespan against sd_a for various heuristics.

available and blocking effects occur. This increase in blocking is partly cancelled by a decrease in blocking effects due to the longer processing times. However, these longer processing times also result in an increase in starvation time. Overall, the result is an increase in flow time and makespan, as was shown in figure 3.4.

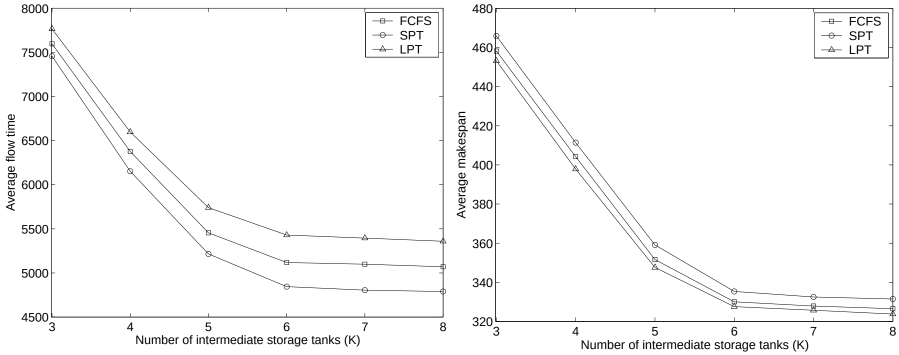
3.5.2 Effect of the number of tanks

In figure 3.5, the flow time and makespan performance criteria are shown for different numbers of storage tanks. With the increase of the amount of intermediate storage tanks, there is (initially) an improvement in these performance criteria. This is mostly due to a decrease in the blocking and starving time encountered. For more than six storage tanks (two for each family), not much more improvement is seen.

However, as we can see in figure 3.6(a), the addition of only one storage tank already results in reducing the amount of unfinished orders to almost zero. With more than six storage tanks, there is even a slight increase in the amount of unfinished orders. This is likely to be caused by an increase in waste, as is shown in figure 3.6(b).

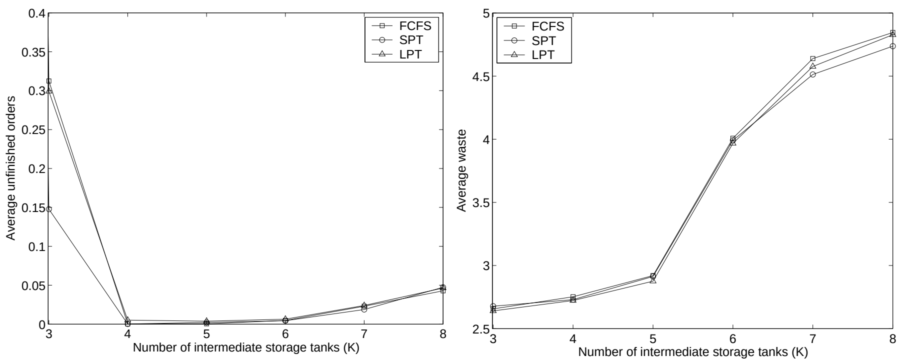
3.5.3 Effect of the storage time constraint

The storage time constraint has a significant effect on the production systems' performance. Until now, we used a maximum storage time of one day. Here



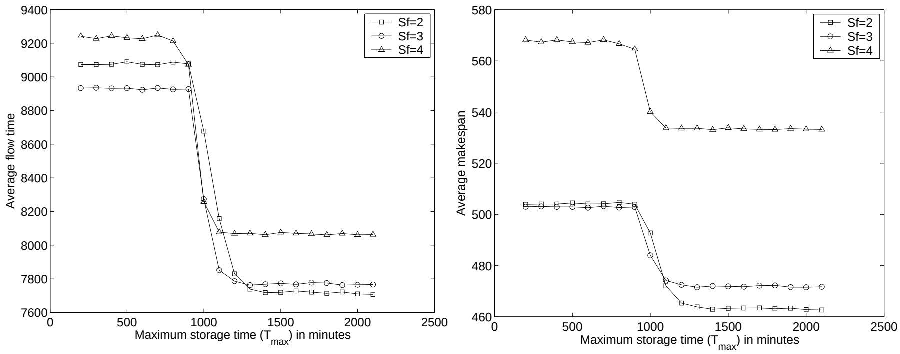
(a) Average flow time (b) Average makespan

Figure 3.5. Average flow time and average makespan against K for various heuristics.



(a) Average number of unfinished orders (b) Average amount of waste

Figure 3.6. Average amount of unfinished orders and waste against K for various heuristics.



(a) Average flowtime

(b) Average makespan

Figure 3.7. Average flow time and average makespan against $T_{\max}$ for various setup frequencies.

we will consider the performance for different values of $T_{\max}$, which we will now state in minutes. The value of $T_{\max}$ also has an important effect on the scheduling; if the time constraint is getting tighter, it is not possible anymore to produce intermediate product for the next day.

As the storage time constraint becomes tighter, it seems logical to reduce batch sizes (increase setup frequency). In this way, smaller amounts of intermediate product are delivered to the storage tanks and can subsequently be packaged faster. Therefore, we look at different setup frequencies. Figure 3.7 shows the flow time and makespan for various values of $T_{\max}$ for three different setup frequencies. The initial setup frequency S_f in our study is 2. In the simulation, we also used $S_f = 3$ and $S_f = 4$.

In the two figures, there is a jump at around 1000 minutes. This change is due to the possibility of storing product overnight when the time constraint is above 1000 minutes. As we can see, being able to 'work in advance' reduces the flow time and makespan significantly.

Several interesting results can be seen in the figures. First, the possibility to store products overnight makes the choice of setup frequency very relevant. For tighter storage constraints, it is useful to increase the setup frequency from 2 to 3. A higher setup frequency results in a lot of setup time and increases makespan.

Secondly, the difference in flow time and makespan with and without the possibility to 'work in advance' is quite big. For the makespan (figure 3.7(b)), note that it is only possible to produce the given orders in a shift of eight hours

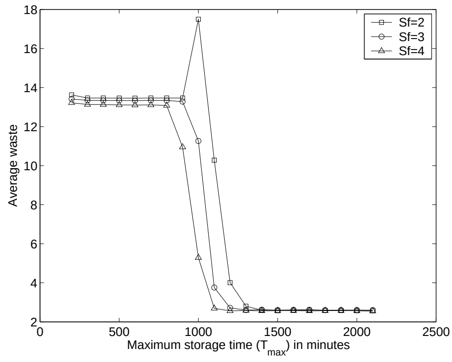


Figure 3.8. Amount of waste against $T_{\max}$ for various S_f.

(480 minutes) if the storage constraint allows to work in advance for the next day. When this is not the case, extensive starving effects at the start of the day negatively influence the performance criteria (as was also illustrated in the example in figure 3.2).

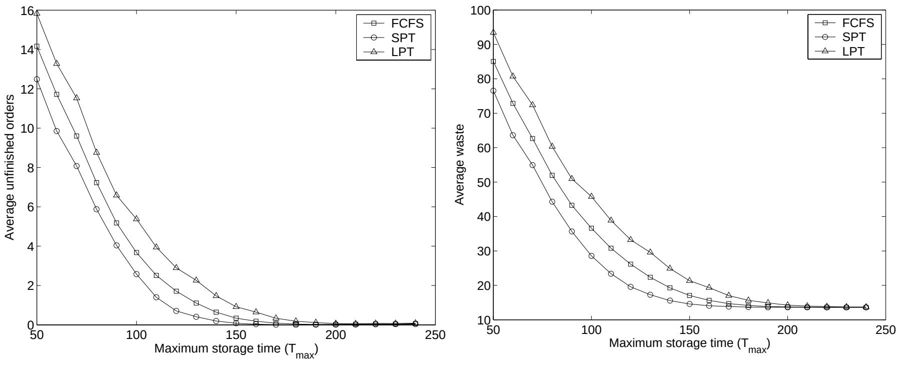
Finally, the amount of waste (figure 3.8) is significantly higher if the storage constraint does not allow storing overnight. This can be explained by the fact that, on every day, all remaining intermediate storage has to be disposed of as waste. Around $T_{\max} = 1000$, it can be seen that the setup frequency has quite an effect on the amount of waste.

For small values of $T_{\max}$, the sequencing rule used is again important. In figure 3.9(a), the number of unfinished orders in shown for different values of $T_{\max}$. It can be seen that with the SPT rule, almost all order are fulfilled for $T_{\max} \geq 160$ minutes. For the LPT rule, this is true for $T_{\max} \geq 200$ minutes. The amount of unfinished orders are also resembled in the amount of waste, as shown in figure 3.9(b).

An explanation for this behaviour can be found in the fact that with the LPT rule the packaging of the first batch can take more time than the production of the following batch. This can in turn cause blocking effects which means that a product already starts its decay before it is even transferred to the intermediate storage.

3.6 Conclusions and further research

In this paper, we addressed intermediate storage tanks with capacity and storage time constraints in a two-stage production system with a batch processor in the first stage and several packaging lines in the second stage. The



(a) Average number of unfinished orders

(b) Average amount of waste

Figure 3.9. Average amount of unfinished orders and waste against $T_{\max}$ for various heuristics.

combination of capacity and time constraints has not been studied before. Our contribution in this paper is seeing how several common-sense scheduling and sequencing rules perform in the presence of these constraints, and analysing how various capacity and time constraints influence the systems performance.

First, the type of sequencing rule in the second stage has significant effects on performance criteria like makespan and flow time. This effect is stronger as the variation in packaging times is higher. Although flow time is minimised by using the SPT rule, the makespan is minimised by the LPT rule. The latter is caused by less starvation in the packaging stage, and can also result in an overall increase in production volume per day. This is an interesting result, because of the intuitiveness of using the SPT rule to empty the storage tanks as soon as possible.

Secondly, we conclude that to manufacture an acceptable number of orders, the number of tanks should be at least equal to the number of packaging lines. When adding one additional tank above that number, almost all orders can be finished in time, but there still are some blocking and starvation effects, which influence the time needed to finish the set of orders. From our analysis, it follows that more additional storage tanks reduce flow time, makespan, blocking time, and starvation time. This effect decreases significantly with every additional storage tank. However, increasing the number of tanks does result in more waste, due to violation of the time constraint. If the number of tanks is more than twice the amount of packaging lines, the increase in waste results in more unfinished orders. This is mainly caused by the need to produce additional batches in the processing stage to replenish the waste. Interestingly, this means that adding tank capacity to the production system could negatively influence some performance measures.

Finally, the storage time constraint has been varied and it clearly shows that it is beneficial to use a different setup frequency if it is not possible to store the intermediate product until the next day. For different storage time constraints, using different sequencing heuristics only has influence for tighter constraints. The SPT rule can cope with tighter storage time constraints than the other rules because of less blocking. There is more starvation, but this does not affect product perishability and waste. As seen earlier, starvation is more important when considering performance criteria like makespan.

The managerial implications of these results could be summarised as follows. First, the intuitive idea of emptying the intermediate storage tanks as soon as possible has a significant drawback in terms of makespan (through increased starvation time). Secondly, the results show that one additional storage tank already has a significant impact on the system performance. Additional tanks can be used to further decrease flow time or makespan, but these investments should carefully be considered. Also, adding tank capacity can lead to more waste and unfinished orders, which is something that needs to be carefully monitored. Third, for tight storage time constraints, emptying the storage tanks as soon as possible does result in the lowest amount of unfinished orders. It turns out that, under tight storage constraints, it is important to realize that both blocking and starvation negatively affect the performance of the production system in terms of flow time and makespan, but only blocking is relevant in causing waste. Finally, an analysis as the one described in this paper is a very useful tool for evaluating the effects of design or expansion decisions.

We realise that the first and the third implication represent a trade-off. If one has to implement a sequencing policy in practice, both implications should be considered and choices have to be made depending on the situation. The development of tools to support managers in making such decisions is an interesting direction for further research.

The results in this paper are based on specific production characteristics. This also raises interesting directions for further research. For instance, we assumed a symmetrical demand pattern for the different product families. Studying the impact of a non-symmetrical demand pattern would be an interesting next step. Also, an interesting suggestion would be to include a distinction between storage tanks that are dedicated to a single product and storage tanks that can be used for multiple products. This would also result in more capacity constraints for the intermediate storage, which could require special treatment in the scheduling and sequencing process. Finally, the analysis could be extended to include other characteristics of the food-processing industry, such as random yields or sequence-dependent setup times.

CHAPTER 4

Prioritization of Products

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Abstract

In the food-processing industry, usually a limited number of storage tanks for intermediate storage is available, which are used for different products. The market sometimes requires extremely short lead times for some products, leading to prioritization of these products, partly through the dedication of a storage tank. This type of situation has hardly been investigated, although planners struggle with it in practice. This paper aims at investigating the fundamental effect of prioritization and dedicated storage in a two-stage production system, for various product mixes. We show the performance improvements for the prioritized product, as well as the negative effects for the other products. We also show how the effect decreases with more storage tanks, and increases with more products.

4.1 Introduction

Typical food-processing companies have a two-stage production process. The first stage consists of processing the product with typical activities such as mixing or heating to change basic food ingredients into basic products. Production can be continuous, but batch-like processes are also frequently encountered. The second stage changes a homogeneous product into a packaged discrete product —often customer-specific— ready for (consumer) use. Mostly, these two stages are distinct in a number of ways, *e.g.* with respect to the labour intensity, the level of capacity utilization, the magnitude and influence of set-ups, and the production rate. In order to find production sequences that are optimal for each stage and to compensate for differences in production rates, the two stages are generally separated by tanks or silos that temporarily store the unpacked, basic product. Typical examples can be found in the dairy industry (Lütke Entrup *et al.*, 2005), the production of beverages (Fey, 2000), the tobacco industry (Van Dam *et al.*, 1998), or the production of breadcrumbs (Van Donk, 2001).

Due to the different nature of the two stages, managing the intermediate storage is necessary to find a balance between opposing demands. The processing stages might prefer long production runs and a specific sequence (like from light to dark colours or from low to high fat), while the packaging stage groups and sequences production based on packaging sizes and aims at combining orders for one customer. Moreover, tanks are usually limited in number and size, as high investments are involved for this type of storage facilities. The time of storing an unpacked product is limited by its shelf life.

A main complication is however that usually the number of products exceeds the number of tanks. Storing a product is thus more than just allocating a production batch to an arbitrary tank. On the one hand availability of products for packaging is needed, leading to the wish to fill as many tanks as possible with basic product. On the other hand, availability of empty tanks is required to enable continuous processing in the first stage of the production process. Planners tend to believe that building extra tanks is the solution for this problem, but, as said before, that is expensive. What makes this situation even more complex is the fact that market demands can be different among products. Lead times for products can be under extreme pressure, which creates a situation where certain products need to get priority over other products. This prioritization often results in fixed assignments —or dedication— of storage to the prioritized product. In this paper, we specifically look at the effects of allocation policies for storing products in tanks, based on product prioritization. The literature in operations management hardly pays attention to this important decision area.

The aim of this paper is to address the effect of prioritization of a product versus treating all products equally. An important result of the prioritization is a specific type of storage allocation: the permanent allocation, further addressed as dedication, of a tank to a prioritized product. This type of storage allocation can also be found in situations where production is hybrid make-to-order (MTO) and make-to-stock (MTS), which is quite common in the food-processing industry (Soman *et al.*, 2004). In those situations, the decision to make a product to stock or to storage is mainly based on its share in the product mix; high-volume products are normally MTS, and low-volume products MTO (see *e.g.*, Youssef *et al.*, 2004). However, this decision can also be forced on the company by market demands. Therefore, we specifically investigate the effects of prioritization by means of dedication policies for various shares of a product in the product mix.

With the present study we are able to assess the overall effect on system's performance of dedicating a tank for low-demand and high-demand products that get prioritized to be delivered within a relatively short lead time.

The overall contribution is to better understand intermediate storage in typical food processing companies in order to improve planning and scheduling in such situations and to improve decision making with respect to the required number of tanks. In general, the situation with intermediate storage can be assessed using a common performance measure like lead time. There are two specific effects of interest: blocking and starvation. Blocking refers to the non-availability of storage tanks for finished product which has to wait in the processing stage, while starvation means idle capacity in the packaging stage due to non-availability of basic product. For instance, in the situation described in this paper, blocking happens if a batch is produced in the first stage, but no intermediate storage tank is available for the product. Then the product has to remain in the batch processor, which delays further batch processing until a storage tank becomes available. Possible prioritization and storage dedication have a large impact on these blocking and starvation effects, which in turn highly influence the behaviour of a production system with limited intermediate storage.

The remainder of this paper is organized as follows. Section 4.2 gives some background information on previous research. In Section 4.3, the production model studied in this paper is described. Subsequently, a deterministic analysis of the production system is presented in Section 4.4. Following that, Section 4.5 presents a numerical study and its results. Finally, Section 4.6 presents conclusions and suggestions for further research.

4.2 Background

In the food-processing industry, reducing lead times is becoming increasingly important as improved customer service is important, especially when dealing with powerful food retail chains (see *e.g.*, Meulenberg and Viaene, 1998). Das and Abdel-Malek (2003) also investigate the effects of a varying lead time in a supply chain on flexible delivery. They state that lead times are one of the main causes for supplier-buyer grievances in a supply chain. As such, reducing lead times creates more pressure on these relationships in the supply chain.

Lead time reduction also relates to the current interest in hybrid MTO-MTS production systems (see *e.g.*, Huiskonen *et al.*, 2003; Soman *et al.*, 2004). For the food-processing industry, a significant share of the production is customer-specific, which often results in a large MTO part in their production system. The reducing lead times interfere with these policies, as it is no longer possible to produce the required product from raw materials within this lead time. The answer usually lies in the storage of certain basic products, which can be packaged for customer-specific orders This results in a hybrid MTO-MTS system at the intermediate storage.

In the literature on hybrid MTO-MTS systems (see Soman *et al.*, 2004, for an overview), demand characteristics (*e.g.*, the share of the product in the product mix) are mostly used to determine whether products should be made to order or to stock. As Soman *et al.* (2004) also argue, other market characteristics are often ignored. In our study, we focus on one specific characteristic: lead time. A short lead time requires MTS at the intermediate storage level and prioritization of the product to be able to meet the required lead time. This is closely related to the work of Sox *et al.* (1997), who denote this required lead time with their service window. Sox *et al.* (1997) then prioritize the MTO products to ensure a good overall customer service. They also note that when the service window becomes very short (compared to the average flow time of the factory), prioritization degrades performance. In our study, the reason for prioritization and dedication is the fact that the required lead time (or service window) is shorter than the average flow time of the factory. Therefore, we explicitly aim at investigating the effect of prioritization ánd dedication (and treating all products equally with flexible storage allocation as the alternative policy) on the performance of a production process.

Next to the prioritization of a product, dedicated storage in the intermediate storage facility is also required to meet the demand. In the literature, we see that several papers address intermediate storage in scheduling. Most papers develop techniques to incorporate these storage tanks in mathematical, mostly MILP-based, scheduling models (*e.g.*, Belarbi and Hindi, 1992; Ha *et al.*, 2000; Rajaram *et al.*, 1999; Yi *et al.*, 2000). In the majority of these papers, the distinction between dedicated and flexible storage is mentioned and considered in the techniques developed. However, this distinction is assumed to be predetermined and known. While the decision to dedicate a storage tank or not is not explicitly discussed, the literature pays some attention to the issues of dedication and flexibility in a qualitative sense.

The main objection against dedication of storage tanks might be the loss of flexibility. One might assume that without dedicated storage, assigning products to tanks is easier and results in higher performance of the overall production system. If each product has its own tank, assignment is even easier. However, in food processing, the number of products usually exceeds the number of storage tanks, so only a partial dedication is possible. In the literature, dedication has hardly been discussed, but flexibility (as being its natural opposite) has been extensively treated. The main question seems to be how much flexibility should be added, as it is assumed that flexibility and flexible equipment are more expensive. For instance, Jordan and Graves (1995) develop principles on the benefits of process flexibility. One of the main outcomes is that a small amount of flexibility can have almost the same benefits as total flexibility. In other words, after a certain flexibility is reached, there are rapidly decreasing benefits when adding additional flexibility. This argument might be transformed for dedication of storage tanks by posing that removing some flexibility could initially be relatively harmless to production performance. However, this is less likely in situations where only a small number of storage tanks are available, as the dedication of one of those tanks removes a significant amount of flexibility.

In summary, the above discussion clearly shows that the effects of prioritization and the decision to dedicate storage have not yet been systematically investigated. For production planning and scheduling —and also for the (re)design of production processes— it is important to understand these effects.

4.3 Production model

4.3.1 Production system

The production system studied in this paper consists of two distinct stages, connected by intermediate storage tanks (see Figure 4.1). The first production stage concerns a (non-preemptive) batch process with a single batch processor with a fixed batch size B. This fixed batch size resembles a technical constraint that is often encountered in the food-processing industry (*e.g.*, kettle size). Due to variability in raw material quality, processing times are variable (see Fransoo and Rutten, 1994).

In the second stage, the intermediate food product is packaged in small and large packaging sizes, depending on customer orders. This translates

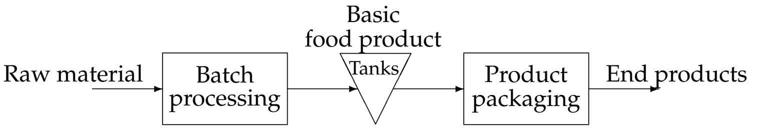

Figure 4.1. General form of the two-stage production process with intermediate storage tanks in the food-processing industry.

into different packaging times; for small sizes more time is required to package a certain amount of product (*e.g.*, more packages moving through the line). This variability influences performance through the blocking and starvation effects mentioned in the introduction.

The intermediate storage consists of K storage tanks, which are used to store N different intermediates. An important aspect is that in a storage tank only one production batch can be stored concurrently —even in case of the same product. This is due to (i) traceability requirements and (ii) not mixing batches to ensure quality. This also makes the size of the storage tanks irrelevant, as long as they can at least contain one batch of product from the processing stage. We assume this is the case.

Furthermore, we make the following assumptions:

- The production system operates in one daily shift of 8 hours.
- Raw materials for the batch processing stage, as well as packaging materials for the packaging stage are always available with negligible lead times.
- Products immediately leave the production system after packaging.
- Transportation time to and from storage tanks is negligible.
- No changeover times for processing, packaging, and storage.
- The quality of the product remains constant in the storage tanks for a fixed period, after which it is discarded at no extra cost (see also Nahmias, 1982; Raafat, 1991, for discussions on modeling perishability).
- Dedication of a storage tank is assumed to be implemented to assure a short lead time for the prioritized or 'dedicated' product.
- Packaging can only start if a customer order has arrived: packaging is customer-specific and order-specific.

4.3.2 Production scheduling

Customer orders arrive continuously during the day. They have several distinct characteristics: (i) product type, (ii) packaging size, and (iii) arrival time.

To study the effect of dedication, we use two different storage policies:

$$P = \begin{cases} F, & \text{a fully flexible policy, in which every tank can} \\ & \text{be used for every product;} \\ D, & \text{a policy in which one storage tank is dedicated} \\ & \text{to a specific (prioritized) product.} \end{cases} \tag{4.1}$$

Without loss of generality, product 1 can be used as the prioritized product with a dedicated storage tank in policy D (also referred to as the dedicated product).

For policy F, the arriving orders are collected in an orderpool until a full batch of a certain product can be produced in the first stage. The 'batch order' is then placed in a FCFS (first-come-first-serve) queue for the batch processor while the orders are moved from the orderpool to the queue at the packaging line.

For policy D, a runout time procedure is used for the dedicated product, because we need to keep this product on stock on the intermediate storage level. The batch order for the dedicated product (a replenishment order) is generated when the runout time of the content of the dedicated tank is smaller than the average batch processing time. The runout time is calculated as follows for product i:

$$RO_i = (I_i - O_i)/D_i, \tag{4.2}$$

where I_i is the inventory level of product i in the intermediate storage, O_i is the number of waiting orders for product i, and D_i the average number of orders arriving per time unit.

Because orders for the dedicated product (in policy D) are immediately packaged from intermediate storage, arriving orders for this product move straight to the packaging queue. For the other ('non-dedicated') products, the orders are processed like in policy F (collected until a full batch is realized). In the batch order queue, the product with dedicated storage has priority over the other products (to ensure the timely replenishment and short lead time).

For the second stage, a basic sequencing rule is used for scheduling the packaging line. The customer order in the packaging queue with the earliest arrival time is packaged first (FCFS). If the required basic product is not (yet)

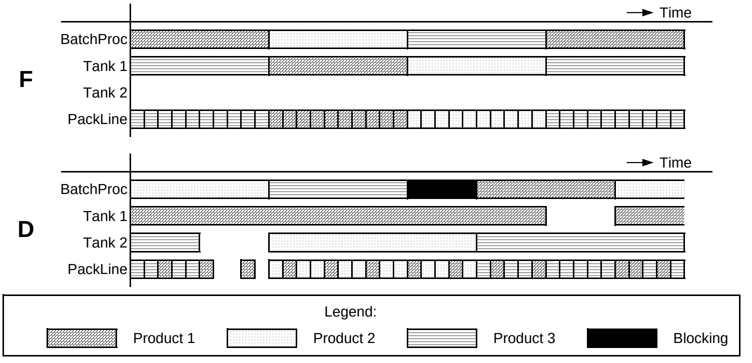

Figure 4.2. Gantt charts that illustrate the effect of dedication of intermediate storage for a product with a share of 33%.

available, the next order in the queue is selected. In case of policy D, this FCFS rule comes second after a priority rule for the dedicated product.

4.4 Deterministic Analysis

To explore the described system, we will perform a deterministic analysis of the behaviour of the simplest system configuration (K = 2 storage tanks and N = 3 basic products) that still enables us to study the effects of dedication for several scenarios with different product shares for the dedicated product. Two storage tanks are needed to be able to distinguish between dedicated and flexible storage; three products are the minimum to have more than one product in the flexible storage. For the sake of simplicity, all possible variability (in order arrivals, processing times, packaging times) is ignored and we assume a utilization of 100%, which we achieve by setting the order arrival rate equal to the production capacity.

4.4.1 Dedication for a product with a share of 33%

The first scenario we analyze is that of equal demand for all products. In Figure 4.2, two excerpts from Gantt charts illustrate the system behaviour. For policy F, we see that a cyclic production pattern emerges, which only needs one of the two storage tanks. The second Gantt chart in Figure 4.2 shows that this situation changes dramatically when policy D is implemented. Several important aspects in this chart are: (i) the possibility to package orders for product 1 from intermediate storage; (ii) the occurrence of blocking at the

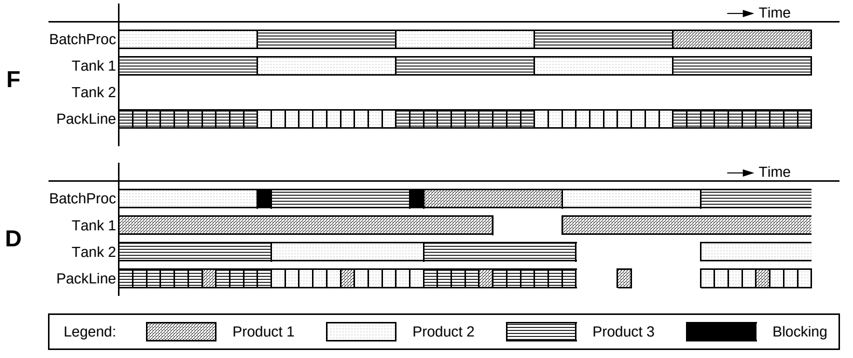

Figure 4.3. Gantt charts that illustrate the effect of dedication of intermediate storage for a product with a share of 10%.

batch processor due to unavailable flexible storage; and (iii) the fact that two storage tanks is getting restrictive, while only one was needed in the flexible case. This results in an unbalanced situation, characterized by an increasing backlog of orders in the long run.

4.4.2 Dedication for a product with a share of 10%

Here, we assume that a storage tank is dedicated to a product that only represents a small fraction of the product mix. Reduced lead times in the supply chain might be the main reason. Figure 4.3 shows partial schedules for policies F and D for a situation where product 1 covers 10% of the product mix, and product 2 and 3 together cover the additional 90%. For policy F, the schedule is still cyclic in nature, albeit that the cycle is getting rather large. In principle, product 2 and 3 are alternating, with one batch of product 1 being produced every ten batches. For policy D, we see that indeed the demand for product 1 can be met in a package-to-order fashion. However, this again results in blocking effects at the batch processor, and significant starvation effects at the time the dedicated tank needs to be refilled. This is again an unbalanced situation, in which the high utilization rate creates an ever-increasing backlog.

4.4.3 Dedication for a product with a share of 50%

Here we assume that a high demand product is stored in a dedicated tank. The reason could simply be the convenience in scheduling if a certain product always goes to a specific tank. This product has 50% of the demand,

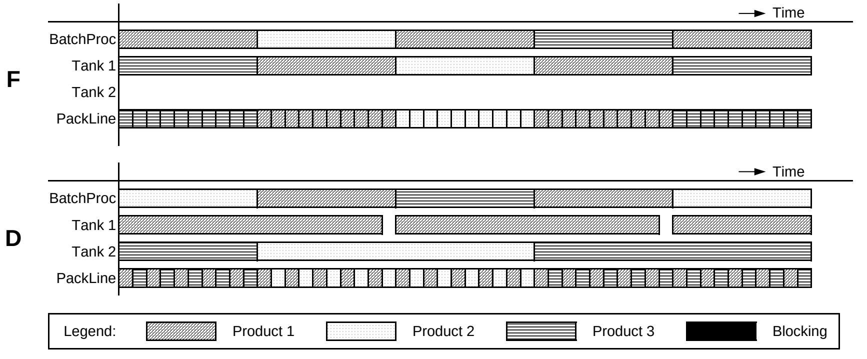

Figure 4.4. Gantt charts that illustrate the effect of dedication of intermediate storage for a product with a share of 50%.

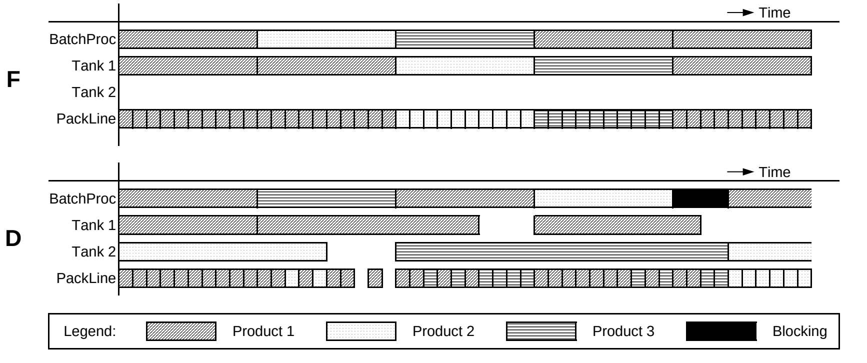

Figure 4.5. Gantt charts that illustrate the effect of dedication of intermediate storage for a product with a share of 60%.

while product 2 and 3 each have 25%. Figure 4.4 shows excerpts from the corresponding schedules. As in the previous scenarios, policy F results in a cyclic schedule (now 1-2-1-3), which only utilizes one storage tank. Policy D, however, shows different results. Here, the package-to-order possibility is again visible, but no blocking occurs at the batch processor. Both storage tanks are highly utilized, and the production system is in balance.

4.4.4 Dedication for a product with a share of 60%

Finally, we study a situation in which the first product has the largest part of the demand: 60%. The other products are each at 20%. Corresponding partial schedules are shown in Figure 4.5. The cyclic schedule still remains for policy

F (here it is 1-1-1-2-3). For policy D, the system is again getting unbalanced through blocking and starvation effects. This makes a growing backlog of orders.

4.4.5 Concluding remarks

The above analysis yields a better understanding of how flexible and dedicated assignment of storage influences systems performance. It shows that flexible assignment of products to tanks (policy F) results in cyclic schedules, while policy D creates more irregular schedules. While lead times for the 'dedicated' product are smaller it negatively affects overall performance and lead times of the other products. For some scenarios (50% product 1), the results showed balanced production systems for policy D. For other scenarios (33% product 1, 10% product 1, 60% product 1), the production system got unbalanced due to blocking and starvation effects, which in the long term results in an increasing backlog of orders.

4.5 Numerical Experiments

To account for variability in processing times, packaging times, and order arrivals, this section will present numerical experiments to further analyze the differences between policies F and D. We study several system configurations, which should provide insight into the interaction between the product mix and the system performance for both policies.

4.5.1 Experimental design

The experimental factors to be varied are (i) the number of storage tanks, (ii) the number of basic products, (iii) the dedication policy, and (iv) the product mix.

The number of storage tanks (K) is varied from 1 to 10 and the number of basic products (N) from 2 to 10. We expect that the effect of dedication is stronger if there are more products than storage tanks, but we also investigated other scenarios. In the paper, we present only scenarios where $N > K$, as these are the situations where the dedication and prioritization has the biggest effects. Furthermore, in practice, the number of products is normally larger than the number of intermediate storage tanks.

The two different dedication policies were already presented in equation (4.1) in section 4.4. For the product mix, 9 different situations will be considered. The share of product 1 (S_1) in the product mix will be varied from 10% to 90%. The remaining products all have an equal part of the remaining share. This is calculated as follows:

$$S_i = \frac{100 - S_1}{N - 1} \qquad \forall i = 2, \ldots, N. \tag{4.3}$$

In the experiments, this is modeled by using the product mix shares as probabilities for the arriving orders.

The main performance criterion used in this paper is average lead time, which is calculated as the time in minutes between the arrival of an order and the completion of that order in the packaging stage. These average lead times are calculated for each of the products, to investigate the effects of different product mixes. Next to lead time, blocking will also be used as one of the important underlying aspects of lead times.

The simulations are performed in MATLAB. Before the experiments are conducted, a warmup period of one month is determined using a graphical method with average lead times. Furthermore, run lengths of one year with 5 replications are determined using a 95% confidence interval for the average lead time. This results in relative half-widths of the confidence interval between 0.8% and 5%. Before the actual simulation runs are conducted, numerous test runs for different parameter settings are performed, while closely watching the system's behaviour for verification purposes.

4.5.2 Parameter settings

Customers orders arrive continuously according to an exponential distribution with $\lambda = 0.16$ (per minute). This resembles a Poisson process with certain interarrival times (6.25 minutes), which is a common way of modeling arrival processes (Law and Kelton, 2000). Together with an average packing time of 5 minutes, this results in an maximum utilization degree of 80% for the packaging line. What percentage is actually realized, also depends on possible blocking effects in the processing stage and starvation effects on the packaging line.

The processing times for the batch processor are sampled from a truncated normal distribution with mean $\mu_a = 50$ (min.) and variance $\sigma_a^2 = 10$ (min.^{2}). This variability is common in the food-processing industry, due to inherent quality variability in the (agricultural) raw materials. The batch size B is 10 units.

For the packaging line we make a distinction between large and small package sizes. As mentioned before, the average packaging time μ_b is 5 min-

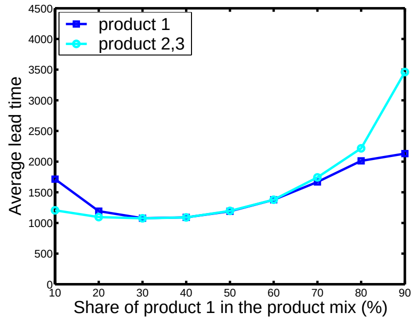

Figure 4.6. Average lead time against S_1 for policy F ($N = 3, K = 2$).

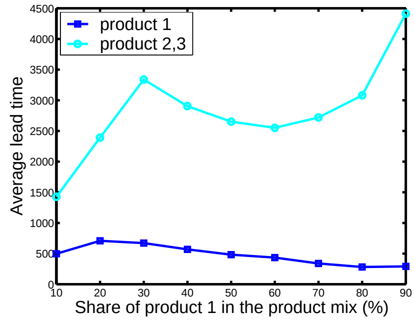

Figure 4.7. Average lead time against S_1 for policy D ($N = 3, K = 2$).

utes, but there are deviations for the package sizes. This deviation b_{dev} is added for small package sizes and subtracted for large packaging sizes. We randomly assign a packaging time $b_{\min}$ or $b_{\max}$ to an incoming customer order, where $b_{\min} = \mu_b - b_{\text{dev}}$ and $b_{\max} = \mu_b + b_{\text{dev}}$. For b_{dev}, a value of 1 minute is used.

4.5.3 Experimental results

As in the deterministic analysis, we start with the most basic system configuration: $N = 3$ and $K = 2$. To obtain further insight, we subsequently compare the results found in the basic configuration with other configurations. In the figures presented in the following sections, products 2 to N have equal curves. This is the result of their equal share in the product mix.

Basic configuration

For policy F, there is a difference in the lead time between product 1 and the other products for small and large values of S_1 (see Figure 4.6). This is the result of the difference in waiting time before a batch can be formed. For example, if S_1 is very high, it takes less time to collect enough orders to form a batch of product 1. This results in smaller lead times. As seen in the deterministic analysis, a batch of product 1 will occur more often in the production cycle. Another aspect is that the more asymmetry there is in the product mix, the higher the lead times are. Partly, this is related to the time until a batch is formed. However, analysis of the amount of blocking shows that for values of 30% and 40% for S_1, the lowest amount of blocking is experienced. We expect this follows from the regular arrival of batch orders in this symmetric situation. A more irregular arrival process is likely to create more variety in the length of the batch queue. This even distribution of the product mix possibly results in an efficient cyclic production schedule, as would be used in practice in similar situations, and is also reflected in the deterministic analysis.

The results for policy D show rather different curves (see Figure 4.7). First, as expected, a significant decrease of the lead time for product 1 is achieved (compared to policy F), and the higher the share S_1, the lower the lead time due to decreasing runout times and less interference with other products. For these other products, policy D results in an overall increase in lead times. Especially when these products make up a major part of the product mix, while product 1 also has a reasonable share. For small values of S_1 (10-30%), an increasing S_1 seems to cause more interference with the production of product 2 and 3. In this situation, these products are still the main products and can only use a single intermediate storage tank. Then, for higher values of S_1 (40-70%), the storage limitation for product 2 and 3 is likely to become less restricting. Their share in the product mix is decreasing and due to a decrease in blocking effects, the lead times are slightly lower. Finally, for very high values of S_1, the interarrival time for orders for product 2 and 3 increases, so the time to collect orders for a batch also increases. Together with the fact that product 1 is becoming very dominant and gets priority in scheduling, this explains the increase in lead times.

Extended configurations

To be able to make more general observations on the interaction between the storage policies and the product mix, we also present some of the results from other configurations. The focus in this section is specifically on policy D. For policy F, the results do basically not change for other values of N and K. For policy D, the influence of having a greater portfolio (larger N) is almost negligible for the dedicated product. For the non-dedicated products, interesting results are found. The main effects can be demonstrated with results for an increasing N (for fixed K) and an increasing K (for fixed N).

For a fixed number of tanks ($K = 2$), the number of products is increased. The average lead times for the non-dedicated products (for $N = 3$ to $N = 6$) are shown in Figure 4.8. For an increasing number of products, we see increasing lead times. This is largely due to the fact that there are longer waiting times before a batch can be formed. Interestingly, there is no increase in blocking or starvation for an increasing number of products. Because batches are handled separately for quality and traceability reasons, the number of

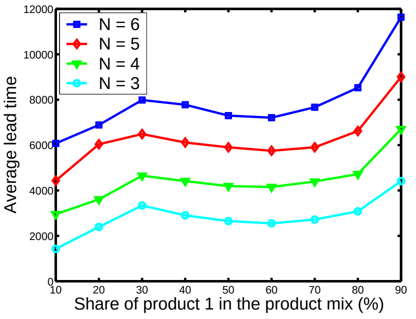

Figure 4.8. Average lead time against S_1 for product 2 to N in policy D for various values of N ($K = 2$ tanks).

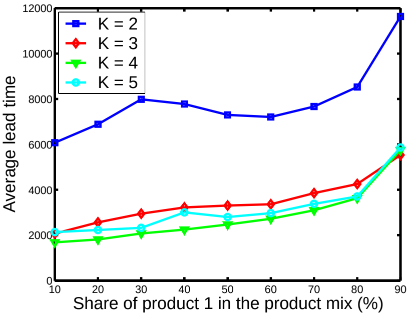

Figure 4.9. Average lead time against S_1 for product 2 to N in policy D for various values for K ($N = 6$ products).

products using the flexible tank does not matter; as long as the products have the same total share in the product mix, the performance is identical in terms of blocking or starvation.

Secondly, the effect of the number of tanks is shown. For a fixed number of products ($N = 6$), Figure 4.9 shows average lead times for the non-dedicated products for several values of K ($K = 2$ to $K = 5$). The figure shows that adding one tank initially results in a large reduction of the lead time. Here, reduction of blocking seems to be the main reason. Changing from $K = 3$ to $K = 4$ and $K = 5$ has far less effect. Furthermore, in the basic configuration we saw high lead times for values of S_1 between 20% and 50% (see Figure 4.7). For configurations with more tanks, this effect disappears.

4.6 Conclusions and further research

This paper studies the effects of product prioritization through dedication of intermediate storage tanks, related to the product mix. We specifically focus on the lead times for the individual products, as we assume prioritization and dedication are used to reduce the lead time for a certain product. Based on the results from the deterministic analysis and the numerical study, the following conclusions can be presented.

First, in a deterministic case, dedication results in irregularity in the production schedules. Also, blocking and starvation effects occur, which did not occur in the flexible case. For high-utilization systems, this results in long-term backlogs of orders.

Secondly, dedicated storage for a product results in significant lead time advantage. Dedication has a negative effect on the performance of the products that use the remaining flexible storage, as expected. For a small system like the basic configuration studied in this paper, there is a significant increase in lead times for these products. However, for configurations with more tanks there are significantly less blocking effects, which decreases the negative effects.

Finally, if all tanks are used flexible, the experimental results show that the performance of the production system benefits from an equal distribution of the products in the product mix. Asymmetry in the product mix seems to lead to an increase of blocking effects, which affect the lead times.

It might be clear that our results are limited as a number of real life issues are not incorporated: the number of products is much smaller than in most real life settings, cleaning and setups are ignored, we use a rather simple scheduling rule, we do not allow packaged product to be stored, etc. Still, we believe that some provisional managerial implications can be derived. Our study helps in deciding if prioritization through dedicated storage for one product will affect the lead time for others and to what extent. Secondly, it shows the positive effect of adding a storage tank on overall performance.

Future research could help in further studying managerial problems in designing this type of production system by analyzing the effects of dedicated storage induced by restrictions on the number of pipes between tanks and packaging lines, investment decisions on extra tanks, etc. Future research can also address a broader range of parameter settings and include other variables such as variability in demand or (sequence-dependent) changeover time for flexible storage tanks. Such characteristics are common in the food-processing industry (Akkerman and Van Donk, 2006a). It seems logical to further validate findings from such more realistic studies with empirical studies.

CHAPTER 5

Product Mix Variability with Correlated Demands

Published as:

R. AKKERMAN AND D.P. VAN DONK (2006), *Product mix variability with correlated demand in two-stage food manufacturing with intermediate storage*, International Journal of Production Economics, accepted for publication.[1]

Abstract

In food processing, market demands are increasingly important, resulting in regular introductions of new products, or special offers. Often, such an introduction or promotional effort affects demand of other products or packaging types. Here we study the effect of such correlated demand. More specifically, the aim of this paper is to study the effect of product mix variability and correlated demand in a two-stage food production system. Results from a simulation study show that increasing correlation on the product level results in an increase in average lead times. A slightly smaller effect is seen for correlation on the package level. Similar results are found for average waste. Increased variability amplifies these effects.

5.1 Introduction

The food industry is becoming a more and more competitive environment where manufacturers have to cope with short due dates imposed by the high market pressure, specifically from large retailers (Dobson *et al.*, 2001; Rundh, 2005). In the food-processing industry, these due dates are especially important, as they are closely related to the best-before dates on the final consumer products. Other distinctive characteristics (see *e.g.*, Nakhla, 1995; Akkerman and Van Donk, 2006a) are the perishability of products and the high quality

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demands. Also, a divergent product structure is common. Only a few raw materials (often agricultural) are processed and packaged to generate a multitude of end products (see *e.g.*, Fransoo and Rutten, 1994). Often, these end products are customer-specific (*e.g.*, mainly in package type, but sometimes also in product type).

Food production mostly consists of two stages: processing and packaging (Van Dam *et al.*, 1993). Between these stages, intermediate storage is present (generally in the form of tanks or silos) to decouple the two stages. To deal with the short lead times and with customer-specific packages for end products, manufacturers often have make-to-order strategies on the packaging level. This puts additional pressure on the production system, as it becomes partly make-to-order (packaging stage), and partly make-to-stock (processing stage). This mixed MTO/MTS situation is related to the customer-order decoupling point (CODP) concept (see also Van Donk, 2001; Olhager, 2003; Soman *et al.*, 2004; Wikner and Rudberg, 2005), which in this paper is located at the intermediate storage tanks between the processing and packaging stage.

The intermediate storage in these industries is normally constrained in capacity *and* time. Capacity is not only constrained by a limited number of tanks, but also because quality demands do not allow concurrent use of a tank (*i.e.*, only one batch can be stored in a tank at a certain time). Time constraints result from perishability of the basic food product, which restricts the time until packaging (see also Akkerman *et al.*, 2006). These storage constraints lead to dependency between the two stages, and often make scheduling a complicated matter in these industries (see also Van Dam *et al.*, 1993).

In the literature, production scheduling of batch plants has been extensively studied in operations management and chemical engineering, mostly using mathematical modeling techniques such as MILP (see *e.g.*, Kondili *et al.*, 1993; Pinto and Grossmann, 1998; Rajaram and Karmarkar, 2004). Most of these approaches become very difficult (*i.e.*, computationally intensive) when considering limited intermediate storage. Furtermore, there is an important difference between batch plants and the type of food production system discussed in this paper: In most cases in the literature, the batches go through all production steps. Here, batches produced in the processing stage are used as inputs for the packaging stage. There are some papers that do treat such systems, like Méndez and Cerdá (2002), who study a make-and-pack facility and develop a MILP formulation, but unfortunately consider unlimited intermediate storage.

In food production, the processing stage commonly involves batch processes that produce various product types (recipes), while the packaging stage usually involves several lines to accommodate multiple package types (*e.g.*, 1/4, 1/2, and 1 liter). These different product and package types result in a product mix with two dimensions. Due to volatile market behaviour in the food sector, the shares in the product mix change regularly —in both the product dimension and package dimension. For instance, new low-fat products are added to the mix, products can be on special offer, or customers (temporarily) buy more large family-sized packages. These changes cause shifts of the workload between packaging lines (package dimension), and cause changing storage tank usage (product dimension).

From the literature, we know that more variability in individual product demand results in a higher variance of the total demand (*e.g.*, Ross, 1997), which in turn can have consequences like lost sales (Andreou, 1990), increasing flow times (Jensen *et al.*, 1999), and increasing safety stocks (Vaughan, 2003). In the two-stage food production system studied in this paper, variability in the product mix causes short-term imbalance in the volumes for the product types and/or package types, which is likely to (i) influence the blocking effects caused by occupied tanks and/or packaging lines, and (ii) affect the amount of waste due to perished product.

Concerning the variability in the product mix, the situation can be even more complicated due to dependency between demands for various product-package combinations. For example, it is well-known that promotional activities within one retail chain affect the turnover of similar products in other chains, resulting in correlations between demands. Also, seasonal demands and new product introductions can result in products which have demand that is positively or negatively correlated with the demand for other products. In the literature, some papers address the issue of correlated demand. The main results are that the effects of variability in demand are stronger when demand is also correlated and that performance is negatively affected if correlations are ignored (see *e.g.*, Zhang, 1997; Vaughan, 2003; Ma *et al.*, 2004).

For the two-stage food production system, the product mix variability can be correlated on two dimension (products and packages), which has not been addressed before in the literature. Also, the interaction between an order-driven packaging stage, a forecast-driven processing stage, and limited capacity intermediate storage facilities is not at all clear from the literature. Although some papers discuss these types of production systems, they mostly concern mathematical optimization approaches (like MILP), which do not

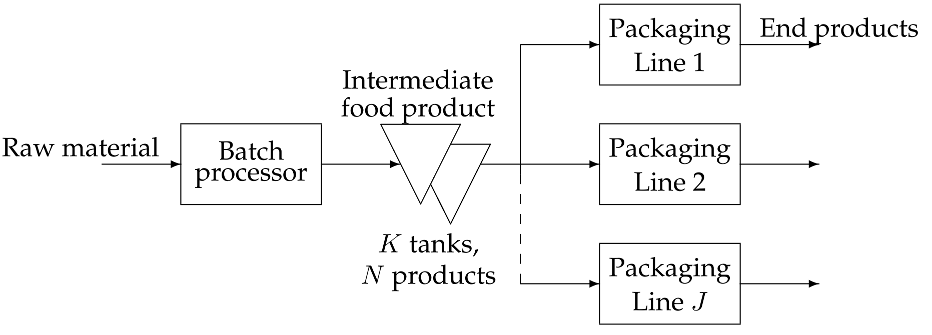

Figure 5.1. General form of the two-stage production process with a batch processor in the first stage and J parallel packaging lines in the second stage.

aim at understanding the basic behaviour and interactions of such systems.

The aim of this paper is therefore to study the effects of product mix variability with correlated demand between product types and package types on the performance of a two-stage food production system with limited intermediate storage. We consider this to be explorative research, and we perform simulation studies to investigate the primary effects.

5.2 Production system

Figure 5.1 illustrates the production environment studied in this paper. In the first stage, a batch process creates N basic food products from (agricultural) raw materials. In the intermediate storage stage, K storage tanks are available to store the basic food products (with $K \leq N$). Here, quality and traceability requirements restrict batches to concurrent storage. In the packaging stage, the basic food products are packaged in M different package sizes or types. More specifically, there are J packaging lines available that can each package all basic food products in one or more package types. Due to technological constraints (*e.g.*, piping), only one packaging line can be connected to a specific storage tank at the same time.

The main characteristic of this production system is the fact that at the processing and intermediate storage level, scheduling is product-oriented, while at the packaging level, it is package-oriented. This results in totally different viewpoints on production scheduling and control. It makes it difficult to create one sequence for the whole production system, as batches are formed on different characteristics (*e.g.*, based on color in the processing stage and based on packaging material in the packaging stage) and often preferred sequences exist for each of the two stages. Also, separate sequences cannot be developed independently due to various dependencies resulting from the capacity and time constraints.

5.2.1 Product mix

We assume equal probabilities for all possible product-package combinations. The variability in the product mix expresses itself in the average order sizes for each product-package combination. These vary from week to week. All orders are considered to have customer-specific packaging demands, which have to be considered in the packaging stage.

As mentioned in the introduction, the weekly average order sizes for the various end products are not necessarily independent. Dependencies are possible on product and package level, and this can cause unequal distribution among product types and package type. These dependencies can occur through both positive and negative correlations. An increase for product i in package j could have several reasons (and effects):

- A random increase in the demand for product i in package j, without affecting other products and packages (no correlation on product level or package level).
- A general increase in demand for product i, in which case demand for the same product in other packages would also increase (positive correlation on the product level). *E.g.*, this could be the result of a short-term increased interest in low-fat products.
- A general increase in demand for package j, which also affects the demand for other products in the same package (positive correlation on the package level). *E.g.*, this could be the case for products in small packages, which are more popular in holiday seasons.
- A specific increase in the demand for product i in package j. This could be at the expense of other products or packages (negative correlation on product level, package level, or both). *E.g.*, this could be the result of promotional activities.

This list is not exhaustive, but such effects can make it hard to continuously realize short lead times. For instance, as shown by Ma *et al.* (2004), overall production variability increases with an increasing correlation between the products. If this increased variability occurs on the packaging level, it could mean significant shifts of the workload between packaging lines.

5.2.2 Production scheduling

The control of the two stages is not fully integrated due to the presence of the intermediate storage tanks. The packaging stage extracts its necessary intermediate product from the tanks. In the batch processing stage, the supply of intermediate product is replenished.

Because of short due dates, the scheduling of the processing stage has to be forecast-driven to safeguard product availability. This is implemented through a runout time procedure. Every time the batch processor becomes idle, the next product to produce is the product with the minimum runout time. This runout time for a product i is calculated by:

$$RO_i = \frac{I_i - O_i}{D_i}, \tag{5.1}$$

where I_i is the inventory level of product i in the intermediate storage tanks, O_i is the amount of product i needed for waiting orders, and D_i the average demand arriving per time unit. Due to the fact that two batches cannot be stored concurrently in the same tank, the batch processor can become blocked if all storage tanks are already in use.

The packaging stage, however, is totally customer-order-driven. Every arriving order is customer-specific and requires a specific combination of product type and package type. Sequencing of these order is performed by using an earliest-due-date (EDD) rule. If a packaging line becomes idle, it will continue with the order with the earliest due date from a list of possible orders. These possible orders are determined by their package requirements (it can be produced on the specific line), and their product requirements (there is intermediate product available in a tank that is not currently supplying another packaging line).

We assume that the setup times involved in the packaging stage are negligible in relation to the packaging times. For the processing stage, setup or cleaning times are included in the batch processing times. This can be done because the processing stage is a batch process that takes a certain fixed amount of time before the product can be transported to an intermediate storage tank (for instance, mixing, fermentation).

The performance of the production system is mainly calculated in average lead times. However, due to the perishability of the intermediate product, the amount of waste is also an important performance measure.

5.3 Product mix variability

End products are distinguished by product type ($i = 1, \ldots, N$) and package type ($j = 1, \ldots, M$), which creates a total of $N \times M$ possible end products. The demand is based on average order sizes d_{ij}. We assume that every arriving order can be for any of the possible end products (with equal probabilities). This means the average *number* or orders is the same for all end products. The average *order sizes* for these orders are not necessarily the same.

The product mix variability between different periods (we use weeks) expresses itself in varying average order sizes. This is modelled through periodically (weekly) changing average demand order sizes d_{ij}. Every week, a new set of d_{ij}'s is generated from a multivariate normal distribution.

5.3.1 Modelling demand correlations

To model possible dependencies between products and packages, we introduce the parameters ρ_{prod} and ρ_{pack}, representing the correlation on product level, and the correlation on package level:

- ρ_{prod}: correlation coefficient for the average order sizes of all end products that have the same product type.
- ρ_{pack}: correlation coefficient for the average order sizes of all end products that have the same package type.

These correlation coefficients can be used to construct a covariance matrix for the generation of new average order sizes.

For example, if $N = M = 2$, the weekly average order sizes d_{ij} are generated from a multivariate normal distribution with means δ_{ij} (combined in Δ) and (co)variance matrix Σ:

$$\Delta = \begin{bmatrix} \delta_{11} \\ \delta_{21} \\ \delta_{12} \\ \delta_{22} \end{bmatrix}, \quad \Sigma = \begin{bmatrix} \sigma^2 & \rho_{\text{pack}}\sigma^2 & \rho_{\text{prod}}\sigma^2 & 0 \\ \rho_{\text{pack}}\sigma^2 & \sigma^2 & 0 & \rho_{\text{prod}}\sigma^2 \\ \rho_{\text{prod}}\sigma^2 & 0 & \sigma^2 & \rho_{\text{pack}}\sigma^2 \\ 0 & \rho_{\text{prod}}\sigma^2 & \rho_{\text{pack}}\sigma^2 & \sigma^2 \end{bmatrix}, \tag{5.2}$$

where σ^2 is the variance for each of the δ_{ij}.

For Σ to be a valid covariance matrix, it has to be positive semidefinite (*e.g.*, Lindgren, 1993). This sets a number of constraints on the correlation coefficients. These constraints can be derived from Σ by calculating its eigenvalues. These eigenvalues have to be nonnegative, for Σ to be positive semidefinite. The eigenvalues are the roots of the characteristic polynomial resulting

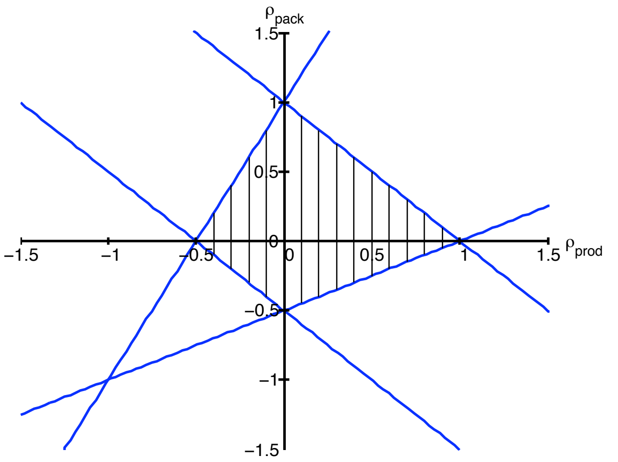

Figure 5.2. Domain for ρ_{prod} and ρ_{pack} following from the nonnegativity of the eigenvalues of the covariance matrix Σ (for the case $N = M = 3$).

from taking the determinant of $\Sigma - \lambda I$, where I is the identity matrix (construction of the matrix Σ is similar to the 2×2 case in equation (5.2)).

For example, if $N = M = 3$, the 9×9 matrix Σ leads to a characteristic polynomial of degree 9 in λ, with four unique roots (the original nine contain doubles)[2]. These four different roots are the eigenvalues of Σ:

$$\begin{aligned}
\lambda_1 &= \sigma^2(1 + 2\rho_{\text{pack}} + 2\rho_{\text{prod}}) \\
\lambda_2 &= \sigma^2(1 + 2\rho_{\text{pack}} - \rho_{\text{prod}}) \\
\lambda_3 &= \sigma^2(1 - \rho_{\text{pack}} + 2\rho_{\text{prod}}) \\
\lambda_4 &= \sigma^2(1 - \rho_{\text{pack}} - \rho_{\text{prod}})
\end{aligned} \tag{5.3}$$

For these eigenvalues to be nonnegative, four restrictions exist for ρ_{prod} and ρ_{pack} (the fifth restriction, $\sigma^2 \geq 0$, is obviously redundant). These four restrictions define a domain in which we can vary the two correlation coefficients in our simulation study. The resulting domain is shown in Figure 5.2.

5.3.2 Effects of product mix variability with correlations

From the discussion in Section 5.1, we know that we can expect certain effects of variability in the (correlated) product mix. Among other things, the vari-

[2]For the sake of completion, the resulting characteristic polynomial is:

$$\begin{aligned}
\det(\Sigma - \lambda I) &= (\lambda - \sigma^2 - 2\sigma^2\rho_{\text{pack}} - 2\sigma^2\rho_{\text{prod}}) \times (\lambda - \sigma^2 - 2\sigma^2\rho_{\text{pack}} + \sigma^2\rho_{\text{prod}})^2 \\
&\quad \times (\lambda - \sigma^2 + \sigma^2\rho_{\text{pack}} - 2\sigma^2\rho_{\text{prod}})^2 \times (\lambda - \sigma^2 + \sigma^2\rho_{\text{pack}} + \sigma^2\rho_{\text{prod}})^4
\end{aligned}$$

ability of total demand is affected, safety stocks requirements change, and fulfillment rates are influenced. All these effects are related to an increasing imbalance in the production system. In our study, this imbalance will likely express itself in blocking and starvation effects on the packaging lines and intermediate storage tanks. These effects influence the amount of waste at the intermediate storage and the lead time performance of the system.

However, more interesting than the variability of demand is the possible correlation between the demands for the individual end products. As was discussed in section 5.2.1, these correlations can exist between product types and between package types and can be positive and negative.

Considering lead times, correlated demand could impact the imbalance in the utilization of the packaging lines and intermediate storage tanks. Positive correlations on the package level could strengthen utilization imbalances on the packaging lines, while negative correlations could smoothen these imbalances. Similarly, correlations on the product level could influence the utilization imbalance between storage tanks. This leads us to the following hypothesis:

(H1) *(a)* Increased positive (negative) correlation on the product level results in longer (shorter) lead times.

(b) Increased positive (negative) correlation on the package level results in longer (shorter) lead times.

Considering waste, the imbalance between intermediate storage tanks will likely affect the storage time of the product. Imbalances between packaging lines are not expected to influence the waste at the intermediate storage. This results in the following hypothesis:

(H2) *(a)* Increased positive (negative) correlation on the product level results in more (less) waste at the intermediate storage.

(b) Correlation on the package level does not affect waste at the intermediate storage.

From previous literature (*e.g.*, Andreou, 1990; Jensen *et al.*, 1999), we know that increased demand variability negatively affects performance. There is no reason to expect that this is any different in the two-stage food manufacturing system we study in this paper. Demand correlations are obviously related to variations in demand, and based on Ma *et al.* (2004), we expect that overall variability increases with correlated demand.

However, to what degree the level of variability and correlated demand interact is a different matter. We formulate the following hypothesis:

(H3) Increased variability leads to an increase of the effects of correlated demand.

These hypotheses are the basis for the numerical experiments discussed in the remainder of this paper.

5.4 Numerical experiments

5.4.1 Experimental design and parameter settings

In the experiments, we initially focus on a situation with $N = K = 3$ and $M = J = 3$. This means that we have 3 basic products that can be stored in 3 tanks. Furthermore, these products can each be packaged in 3 different package types (each on a separate packaging line). This creates a total of 9 end products. We chose this configuration to have a minimum amount of interaction between different products and packages, while still having a reasonably simple system.

Customer orders arrive according to an exponential distribution with $\lambda = 0.06$ orders (per minute). This results in a Poisson process with an interarrival time of 16.67 minutes. With equal probabilities, an arriving order can be any product type i, and package type j. The order size is sampled from a normal distribution with mean d_{ij} and coefficient of variance $CoV_d = 0.2$ (*i.e.*, the variance depends on d_{ij}). As described in Section 5.3, the parameters d_{ij} get assigned new values every week, to model the variability in the product mix. These d_{ij} are sampled from a multivariate normal distribution, as was outlined in section 5.3.1. The overall mean demands δ_{ij} are set to 50, with a coefficient of variance $CoV_\delta = 0.2$. The normal distributions are truncated to exclude possible negative values, although this seldomly occurs.

Processing times of the batch process are normally distributed with mean $\mu_b = 300$ (minutes), and $\sigma_b^2 = 60$. The batch processor operates with a fixed batch size $B = 1000$. For the packaging lines, we also assume normally distributed packaging times with mean $\mu_p = 0.24$ (minute per single package), and $\sigma_p^2 = 0.06$. Here again, the distributions are truncated to exclude possible negative values. In this case, the trucation causes a slight increase in the averages (mainly for the packaging times) but this effect does not impact the results presented in this paper.

The main parameters in our experiments are the parameters underlying the product mix variability and the dependencies on product and package level: ρ_{prod}, and ρ_{pack}. They can be varied in the domain specified in Section

5.3.1 to study the effect of these dependencies on lead times and waste.

The simulation experiments were performed in MATLAB. As we consider an empty system at the beginning of each week, the simulation has a run length of one week. Before the experiments were conducted, the necessary number of replications was determined using a 95% confidence interval for the average lead time. The number of replications was chosen in such a way as to result in relative half-widths of the confidence interval below 5%.

5.4.2 Experimental results

In the previous paragraph, we determined that ρ_{prod}, and ρ_{pack} could be varied in the domain determined in Section 5.3.1. For $M = N = 3$, this means the individual correlations can be varied from -0.5 to 1, if the other correlation is assumed to be zero. The first experiments we undertook had these configurations.

Correlated demands

Concerning the performance of the system, average lead times and average waste was calculated for each configuration. For correlation on the product level ($\rho_{\text{prod}} \in \{-0.5, 1\}$) the results for average lead times and average waste are shown in Figure 5.3(a) and (c). It can be seen that higher correlation on the product level results in longer lead times and more waste. This also means that negative correlations have a positive effect on performance. These effects are likely caused by the amount of imbalance between workloads between storage tanks, resulting in an increasing amount of starvation on the packaging lines due to product unavailability. This confirms hypothesis H1(a) and H2(a).

For correlation on the package level ($\rho_{\text{pack}} \in \{-0.5, 1\}$), we see a very similar behaviour as with correlation on the product level. As shown in Figure 5.3(b) and (d), average lead times and average waste also increases with correlation on the package level. Here, imbalance between packaging lines is experienced, which has the demonstrated effects. This confirms hypothesis H1(b). In hypothesis H2, we did not expect increasing waste from an increasing correlation on the package level. As it turns out (See Figure 5.3(d)), there is also a significant result of increasing correlation on the package level, which rejects hypothesis H2(b).

The results discussed until now concern the effect of either correlation on the product level *or* on the package level (while the other was kept zero). To

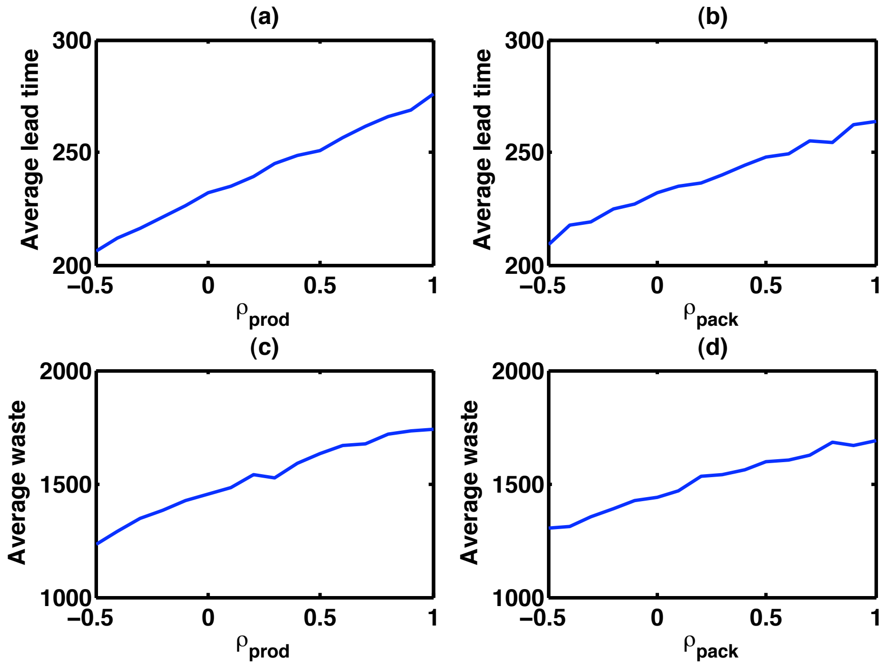

Figure 5.3. Effects of ρ_{prod} and ρ_{pack} on average lead time and average waste.

study the interactions between correlations on the product and package level, we extended the experimental design to include all possible combinations of correlations on both levels (which were identified in Figure 5.2). For the effect of the correlation coefficients on average lead time, the results are shown in Figure 5.4.

The 3D graph in Figure 5.4 suggests that there is no proof for interaction effects between the two correlations. This means that the combined effect of correlation on *both* the product and the package dimension is just the sum of the individual effects. Experiments with the performance criterion waste show similar results.

Demand variability

The final hypothesis stated in Section 5.3.2 concerned the interaction between correlated demand and demand variability. To study this interaction, we repeated the experiments in the previous section for a number of values for the coefficient of variance of weekly demand averages ($CoV_\delta = \{0.1, 0.2, 0.3\}$). The results for average lead time are shown in Figure 5.5.

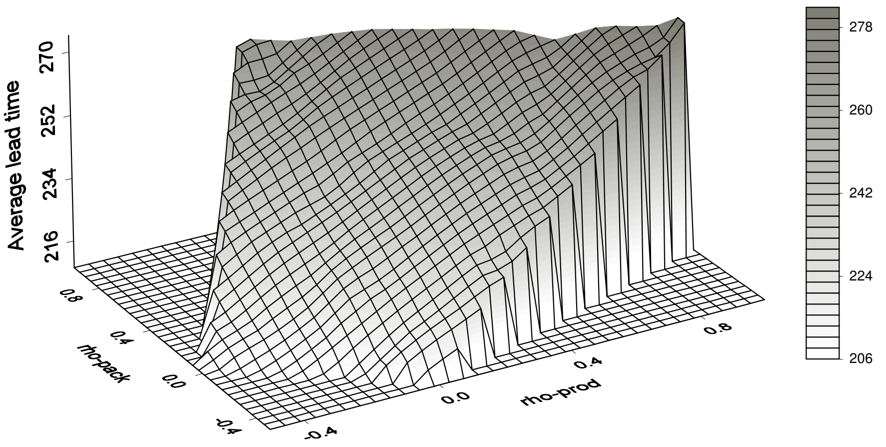

Figure 5.4. Effects of ρ_{prod} and ρ_{pack} on average lead time.

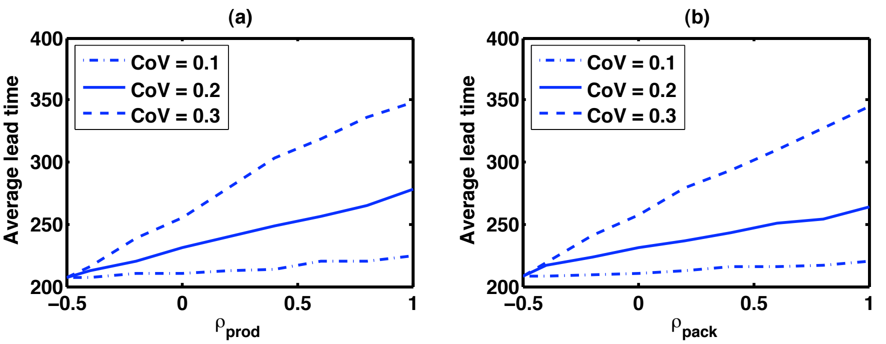

Figure 5.5. Effects of ρ_{prod} and ρ_{pack} on average lead time for different demand variability.

The experimental results show that the effect of demand correlation indeed increases with an increasing coefficient of variance for the average weekly demands, confirming hypothesis H3. Reasoning from a situation where there is no correlation, this also suggests that the effects of variance decrease in the case of negative correlations. Results for the performance criterium waste show a similar result, and are therefore omitted. Concerning the underlying blocking and starvation effects, it turns out that a higher coefficient of variance results in a higher overall level of starvation on the packaging lines.

5.5 Conclusions and further research

This paper studies the effects of product mix variability with dependency between product types and package types in a two-stage food production with intermediate storage. A simulation study is performed to investigate these effects in an explorative way. Dependency between product types and package types is modeled by defining a correlation coefficient for each of these dimensions. In this way, it easily translates to reality, and it also creates useful modelling possibilities.

The paper shows that increasing correlation on either the product level or package level increases average lead times. The same result is found for average waste. For both performance measures the effects of correlation on the product level are slightly larger than on the package level. The paper also shows that increased variability results in an increase in the effects of correlated demand. This also means that negative correlations can reduce the impact of demand variability.

These results have several practical implications. First, the need to include information on correlated demands in managerial decision-making depends on the level of variability. For instance, when a firm has to cope with highly volatile demands, it becomes very interesting to include information on correlated demands in decisions involving the product mix (*e.g.*, order acceptance, adding new products, assigning products to plants). Secondly, when considering demand correlation in decision making, the effects of correlation on the product or package level are about the same, in terms of average lead times and average waste.

A limitation of our study can be found in the system configuration. Although we believe the results we found are relatively generic, other system configurations might show stronger (or weaker) effects of correlated demand and variability of demand. For instance, the product mix is currently chosen symmetric, which is a very specific configuration. In practice, a large part of the demand is often concentrated in only a small part of the product mix. Although this will also be resembled in the available capacity, it will be an interesting opportunity for further research. Other configuration aspects, like the size of the production system and the number of products, can also be interesting topics for further study.

A second limitation is the use of fairly myopic scheduling procedures in both the batch processing and the packaging stage. Therefore, another opportunity for further research is the development and analysis of more intelligent scheduling procedures. For the batch processing stage, a good forecast is important to keep providing the packaging stage with enough (and correct) products. Under low demand variability, a simple cyclic schedule would suffice and is normally better in terms of setups. But with more demand variability or positive correlations on the product level, it could be necessary to abandon cyclic production. This would likely result in a procedure that combines cyclic schedules and runout time rules in an intelligent way. For the scheduling in the packaging stage, better sequencing rules (combining *e.g.*, due dates, processing times, shelf life, ...) could likely be developed to increase performance.

CHAPTER 6

Reduction of Product Losses

Introductory note

The degree of connectivity between two production stages is an important aspect in the management of operations. Differences and volatility of production speeds have more influence on performance if two stages are more strongly connected. This especially concerns packaging speed, as packaging equipment is more prone to disturbances and will therefore be more volatile.

In the previous chapters, simulation results were presented for two-stage production systems with intermediate storage. In the production systems that were studied, the intermediate storage decoupled the processing and packaging stage to a large extent. For the production system in this chapter, the decoupling is only minor, or in other words: the two production stages are strongly connected.

Production disturbances are an important aspect in our research framework. For any situation, the analysis of disturbances is relevant in the reduction of product losses. But due to the strongly connected production stages, their impact becomes even bigger; the time between a disturbance in the packaging stage and a resulting effect in the processing stage is relatively small.

The strong connection is therefore also the main reason for developing the simulation tool presented in this chapter. The tool simulates production on the operational level, because this is the level where the process interactions occur that lead to the realization of product losses. Even for managerial decisions made on a higher level (tactical/strategic), the simulation of operational interactions is therefore necessary.

Although the research framework is applicable for a wide range of production systems, the importance of the production disturbances is partly dependent on the degree of connectivity between the production stages. Especially for strongly connected production systems (like the case study presented in this chapter), the resulting decision support tool can be valuable in the analysis and reduction of product losses.

The remainder of this chapter is published as:
RENZO AKKERMAN AND DIRK PIETER VAN DONK (2006), *Development and application of a decision support tool for reduction of product losses in the food-processing industry*, Journal of Cleaner Production, accepted for publication.[1]

Abstract

In food-processing industries, reduction of product losses is important for improving profitability and sustainability. This paper presents a decision support tool for analyzing the effects of planning decisions on the amount of product losses in the food-processing industry. We created a research framework to collect and analyze data, supporting the development of an Excel-based decision support tool that helps to evaluate different scenarios for the planning decisions and production parameters. The tool was developed in co-operation with and implemented in a real-life dairy plant, where the tool was able to reduce the planning-related losses by nearly 20%. But an equally important result is the insight gained on the interactions between processing, packaging, and intermediate storage. The framework and tool can easily be implemented in other situations.

6.1 Introduction

In the process industries, waste and product losses are important due to environmental and economical requirements. In the food-processing industries, due to low margins, and high value of raw materials, product losses can be an interesting starting point for reducing costs and improving profitability. It will lower the amount of raw materials used, decrease the amount of rework and improve the quality of the end product. Furthermore, environmental performance is also becoming a means for gaining competitive advantages (see *e.g.*, Bansal and Roth, 2000; Faulkner *et al.*, 2005). For the food-processing industry, reduction and reuse of organic residues are the two major environmental challenges recently identified by Maxime *et al.* (2006).

Concerning product losses, we can differentiate between planning-related losses and unpredictable losses. The type of production process we present in

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this paper concerns a very common two-stage process with a processing and packaging stage (and intermediate storage). Unpredictable losses are caused by production stops due to disturbances; planning-related losses are caused by stops due to setups, intermediate cleaning operations, full intermediate storage tanks (stops the processing stage), and tanks running empty (stops the packaging stage). The amount of losses is not that obvious, because of the capacitated intermediate storage tanks; the interactions between processing and packaging are not straightforward (see also Van Dam *et al.*, 1993).

For production management, it is specifically interesting to know or estimate product losses before production starts. Due to the interactions between processing equipment, intermediate storage tanks, and various packaging lines, prediction of product losses is not straightforward. A large variety in stock-keeping units (SKUs) and batch sizes, combined with interactions between process parameters like capacitated intermediate storage tanks and production speeds of the processing and packaging stage, create a situation where the impact of planning decisions on product losses is not clear to production management. The possibility to estimate these losses allows production managers to change production parameters like batch sizes and sequences to be able to evaluate its effect on product losses. To the best of our knowledge, studying product losses from a planning perspective has not been presented before in the literature.

The objective of this paper is to develop a decision support tool to analyze product losses in the food-processing industry. This includes the development of a research framework, which also yields valuable results by itself. The decision support tool is designed to estimate the product losses for a period of planned production (*i.e.*, choice of batch sizes, capacity assignments) and facilitates scenario analysis. We also applied the proposed decision support tool in a case study to show its potential for reduction of losses.

The paper is structured as follows. First, we address the research framework and relate this to existing literature. Then, we explain the methodology applied in the case study. Subsequently, the development of the decision support tool is presented in detail. Next, we describe the deterministic simulation study we performed with the decision support tool. Finally, we discuss the findings, their implications and limitations, and the opportunities for further research.

6.2 Theoretical background

So far, product losses have been studied mainly from a point of view of reducing waste and reducing the environmental pressure. Especially, the reduction and re-use of wastewater has had quite some attention in the literature, mainly from a more engineering-oriented perspective (see *e.g.*, Mann and Liu, 1999; Puigjaner *et al.*, 2000). For the food-processing industry, approaches are also mostly geared towards biological and technical improvements, for instance in the case of beer production as recently surveyed by Fillaudeau *et al.* (2006).

Within the production management literature, waste management in process industries has been largely ignored: most work has been done in the manufacturing and remanufacturing of discrete products (see *e.g.* Guide *et al.*, 1999; Guide, 2000). Flapper *et al.* (2002) and French and LaForge (2006) are among the first to systematically explore a specific aspect of waste management in the process industries: reuse. Next to the reuse of product losses, the reduction of losses is a major challenge in the food-processing industry (Maxime *et al.*, 2006).

We believe the reduction of product losses through improved planning decisions to be a promising direction in this field of research. First of all, this directly reduces losses, but as a secondary effect, a larger percentage of the remaining losses can be reworked within the quality boundaries, due to additional planning insights.

In process industries, a significant part of product losses is related to setups of equipment when changing from one product to another (see also Flapper *et al.*, 2002). This would advocate a situation where the number of setups is minimized —and batch sizes chosen as large as possible. However, in recent years, there has been a trend towards smaller production batches to improve Just-In-Time (JIT) practices. Although, most of these studies concern discrete processes, Mehra *et al.* (2006) found that this also applies to process industries. This trend might result in more product losses and it makes losses an important issue to consider.

6.2.1 Research framework

The research framework we developed for this study is presented in Figure 6.1. The approach chosen in this paper is related to the approach by Van Donk *et al.* (2005) for the make-to-order versus make-to-stock decision. The main points in the framework we present are to study the production characteris-

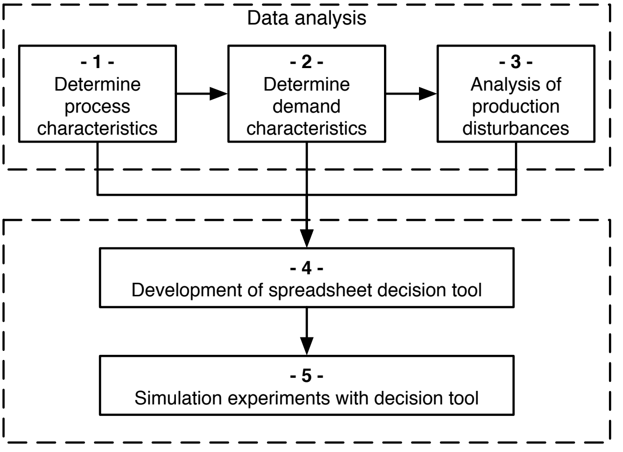

Figure 6.1. Research framework for the creation of a decision support tool for product losses.

tics, investigate the demand, and to make an in-depth analysis of production disturbances and breakdowns. These results are used in the development of a deterministic spreadsheet simulation of the production system, which is subsequently used to study the effect of various planning decisions on product losses. We can, for instance, analyze different parameter settings with regards to efficiency, planning period and the production system configuration.

First, we identified process characteristics, consisting of the structure of the production process and the task of production control (Akkerman and Van Donk, 2006a). This analysis is the basis for understanding and improving production control. The necessary data were gathered from process diagrams, existing information systems (*e.g.*, Enterprise Resource Planning (ERP) systems), and interviews with production planners and process engineers.

Secondly, we analyzed demand characteristics. To analyze this, we used procedures based on the approach of D'Alessandro and Baveja (2000), where demand variability and average demand were used to create product segments. Historical demand data can normally be retrieved from information systems at production or sales departments. In their study, the authors created product segments to decide between make-to-order and make-to-stock strategies for each of the segments. They did this graphically by plotting average weekly demand on the x-axis and its coefficient of variance on the y-axis. Furthermore, they used the results to reassign products to different plants. In this paper, demand variability and average demands were relevant in the realization of batch sizes and the number of changeovers. For product losses, the number of changeovers was a very important variable; starting and stopping production is one of the main causes for product losses. Compared to D'Alessandro and Baveja, we focused more on regularity of demand, to be able to show possibilities for combining batches. This also meant we slightly changed the graphical method. Here, we used the average time between two orders for the same recipe (which we labeled inter-arrival time) as a measure for regularity on the y-axis. Also, because average weekly demand gave an unrealistic idea of batch sizes for recipes that are not ordered every week, we changed the variable on the x-axis to the average order size.

Finally, production disturbances on the packaging lines are studied based on machine failure codes retrieved from production control software. As these (stochastic) disturbances are the cause of the unpredictable losses, an analysis of all production disturbances is a necessary third step in the analysis.

The decision support tool we developed is designed for determining the amount of product losses for a capacity assignment provided by the user. This means we are not aiming at automating any planning decisions, but only at providing insights into the effect of these decisions on product losses. In the process, it also results in a better understanding of the production process and the interaction between different production units. According to Olhager and Persson (2006), this last issue is one of the main reasons for using simulation studies in manufacturing environments. Olhager and Persson further stated that a thorough understanding of the nature of the manufacturing operations is one of the factors in the search for operational excellence. With the decision support tool presented in this paper, we specifically aim at improving this understanding.

The implementation of the decision support tool is performed in the spreadsheet program Microsoft Excel using the Visual Basic programming language. We feel that this greatly improved user acceptance, as virtually all possible users have experience with the software. Thiriez (2004) argues that better user acceptance is caused by the availability of Excel on most computers and by the fact that the user can see (at least partially) how the model works, which makes her/him feel closer to the model and less reluctant to actually use it.

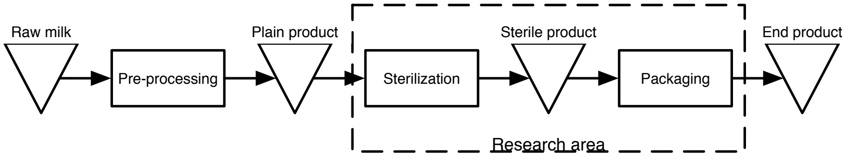

Figure 6.2. Outline of the production system in the case study (including the main research area).

6.3 Case study

The case study discussed in this paper concerns a dairy plant, which weekly uses 3-4 million litres of raw milk in the production of over 200 different SKUs for a variety of consumer markets. The main characteristics of the SKUs are recipe and package size. These two characteristics also determine (to a large extent) the required processing and packaging steps.

Initial results from the data analyses, as well as the final results from the simulation study, were presented on a regular basis to a project group consisting of operations management and operations research (OM/OR) faculty, production planners, process engineers, the plant manager, and other relevant parties. This close cooperation ensured the validation of our research findings and gave opportunities for data triangulation to ensure internal validity (see *e.g.*, McCutcheon and Meredith, 1993).

6.3.1 Process characteristics

In this paper, we do not describe the full process analysis in our case study, but limit the contribution to some general points that are necessary for discussion in the remainder of the paper.

The three main steps in the production process are pre-processing, sterilization, and packaging (as illustrated in Figure 6.2). For the product flow through the plant, this means conversion from raw milk collected from farmers to end products that are shipped to retailers. Before and after the sterilization process, intermediate storage tanks are present to hold prepared recipes and sterile products.

Because the focus of this research was on the reduction of product losses from a planning perspective, we also identified all the places where product losses occurred, how much losses occurred in each situation (determined by taking samples), and whether these losses were in any way influenced by planning decisions. This analysis resulted in a focus on a specific part of the plant (shown in Figure 6.2), where 75% of the losses occur and where most of the planning decisions are made. The resulting part of the production system concerns the sterilization and packaging of products. An important remark is that these two production stages are quite different in the way they handle products. The sterilization process is a batch process, producing sterile products for transfer into the intermediate (sterile) storage tanks. The packaging process consists of several packaging lines that can each package a certain package size. In general, the sterilization process can be considered as the bottleneck and is therefore, a leading factor in production planning. Normally, several packaging lines are connected to each sterilization process, to balance production speeds and to be able to produce various packaging sizes.

Concerning the scheduling process, the most important information is that scheduling is performed on a weekly basis, mainly based on orders received from the centralized planning department of the business unit. The orders are received on SKU level, where package sizes, labels, and recipes are differentiating elements. For the production scheduling, the orders are aggregated on recipe level. The major changeover efforts are between recipes. The required package sizes only determine which packaging lines can be assigned (can be more than one line for a recipe). Changing between labels can be done inline, and is relatively effortless.

The setups are very important in determining the amount of product losses. When changing between recipes, piping is emptied, the equipment must be sterilized and the new production started. During these steps significant product losses are incurred. Next to the losses occurring during changeovers, losses can also occur during production when:

- The intermediate storage tank is full and the sterilization process has to be stopped and restarted;
- The intermediate storage tank is empty and packaging lines have to be stopped and restarted;
- The sterilization process or one of the packaging lines reaches its maximum running time and the equipment has to be cleaned and again sterilized to ensure product quality.

In all of these cases, product losses are incurred, which we labeled as planning-related losses. The amount of these losses is hard to predict, because it is partly dependent on the realized efficiency of the packaging lines, which mainly depends on the production disturbances, which have also been studied in detail and are discussed below. For instance, if a certain packaging line has a low realized efficiency, products will accumulate in the intermediate storage tank until the tank is full and the sterilization process has to be stopped and restarted. Later in this paper, we present a spreadsheet simulation of the production system to estimate these planning-related losses.

6.3.2 Demand characteristics

For analyzing the demand characteristics, we collected historical order data from existing information systems. This data consists of one year of weekly order sets on SKU level. This was coupled with the classification of products to gain information on a recipe level.

Initially, we performed the analysis as suggested by D'Alessandro and Baveja (2000), plotting weekly average demand for recipes on the horizontal axis and the coefficient of variance on the vertical axis. By analyzing one full year of order data, it was clear that three clusters of recipes were produced:

- Recipes with high average weekly demand and relatively low variability;
- Recipes with intermediate average weekly demand and a medium variability;
- Recipes with low average weekly demand and high variability.

One of the main determinants for the coefficient of variance is the number of weeks in which there is no demand for a certain recipe. For the three clusters found, this means that the low-variability recipes are ordered every 1–2 weeks, the medium-variability recipes every 1–2 months, and the high-variability recipes once or twice a year.

As described in the research framework, we propose a slightly different graphical method than D'Alessandro and Baveja. The result is shown in Figure 6.3; the vertical axis has been cut off at 6 weeks, as any recipe with a longer interval is incidental. In this way, we feel we can show the potential improvement by combining batches. For instance, if a certain recipe has small order sizes, but is received almost every week (the lower left corner of the figure), it is useful to see whether it is possible to combine some of these orders to increase batch sizes. In our case study, this was not always possible due to the shelf life of the product. However, for some products (with longer shelf life), it was possible to combine these orders to form larger batches. The general expectation is that this will lead to a decrease in product losses, but this

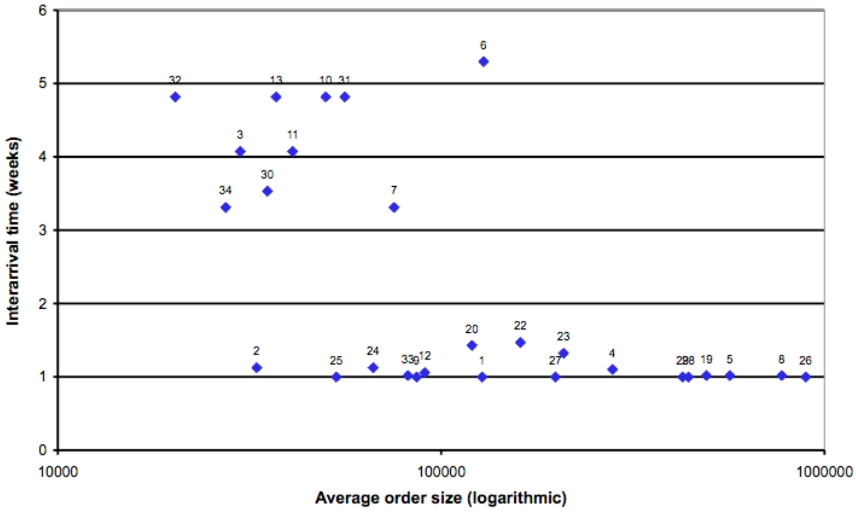

Figure 6.3. Analysis of demand variability. By plotting the time between two orders for the same recipe against the average order size, the figure provides insight in the regularity of demand and the opportunities for combining batches.

is difficult to quantify. Therefore, we chose to add the spreadsheet simulation to our study.

6.3.3 Production disturbances

Concerning the production disturbances, we used information from an information system that registers all production stops with accompanying reasons. These data sets were used to study how the failures were distributed among the production units, and to what extent these stops can be related to planned production. Ideally, this would result in a direct relationship between the production stops and planning characteristics like the amount of SKUs produced in a certain period or the runtime of the production units. For instance, the number of production failures can be expected to be higher when starting equipment for a new batch, and therefore, the number of production stops could decrease as average batch sizes increase.

In our case study, production failures were present on the packaging lines. Here, a large array of equipment for packaging, labeling, wrapping, etc. causes frequent production stops. For the sterilization processes and the intermediate storage tanks, production failures do not exist. Unfortunately, it was not possible to compare failure behaviour and planned production on a detailed level. Therefore, we resorted to regression analysis to identify relationships between a number of aggregate measures, such as the total number of stops per week. From the information available, the expectation is that the main contributing factors in the number of stochastic stops are the production volume and the number of SKUs produced within this volume. The production volume determines the amount of production time, and thereby, affects the number of expected (stochastic) breakdowns. The number of SKUs is included because the expectation is that production failures would be more likely to happen after a minor changeover on the packaging line (to change product labels or tray sizes).

Using multivariate regression analysis, we determine that only the production volume has a significant effect and thus can be used to estimate the amount of product losses. Interestingly, no significant relation between the number of SKUs and the amount of production stops was found. The estimate can be implemented by an average number of disturbances per time unit for each of the packaging lines, which is a simple but intuitive procedure. In the decision support tool presented in the following sections, the final overview of product losses shows this estimate next to the calculated number of planning-related losses. In this way, the tool was able to provide an overview of all product losses within the research focus.

6.4 Spreadsheet decision tool

The tool is basically a deterministic spreadsheet simulation, implemented in Visual Basic for Microsoft Excel. It consists of four steps (outlined in Figure 6.4), which use company data. In the first two steps, user input is necessary. The general outline can be summarized as follows. First, a set of production orders in inserted on SKU level. Secondly, these orders are aggregated on recipe level. Here, batches are formed and capacity assignments are made (user input). The third step is the actual deterministic simulation, where the expected realized production is depicted in Gantt charts. The fourth step includes the calculations of the expected planning-related product losses based on all the starts and stops of the production units shown in the Gantt charts.

Since we were specifically not intending to develop a scheduling tool, the batching and capacity assignments were included as user input. In this way, the model can be used to perform *what-if* analyses for different scheduling decisions. In the following sections, the four building blocks of the decision support tool are described in more detail.

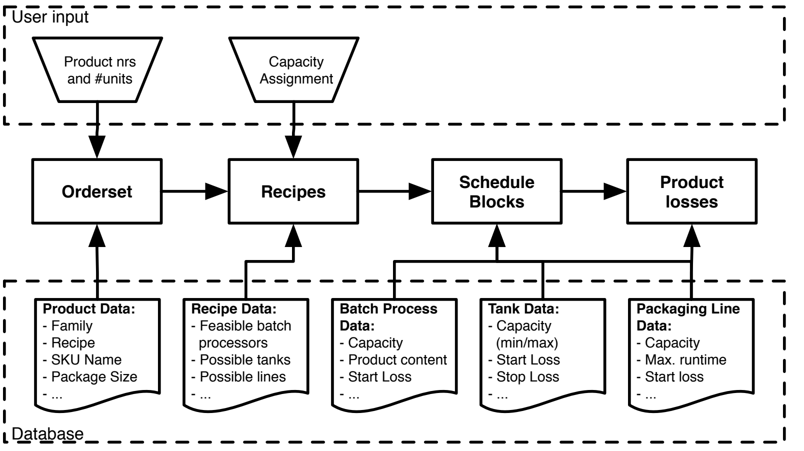

Figure 6.4. Structure of the decision support tool, consisting of four steps: (1) production orders, (2) capacity assignment on the recipe level, (3) the graphical representation of the simulated production, and (4) the calculation of expected product losses. User input and company data are a necessary input throughout the process.

6.4.1 Step 1 — Orderset

Here, order data can be inserted on SKU level, which is also the way the data are currently delivered from the central planning department. Because of links to the product database that contains all relevant product information, such as recipe, package size, etc., the SKU name can be added automatically when entering a product number. Automatically, the SKU amounts are transformed into uniform measures like litres or kilos.

6.4.2 Step 2 — Recipes

After product data are obtained on the SKU level, an aggregation is performed to obtain data on the recipe level. These recipe orders have to be scheduled on the various production units (batch processors, the intermediate storage tanks, and the packaging lines). Here, we come to the final and most important user inputs. Batching decisions and production unit assignments can be made for each recipe. If necessary, recipes can be split into several batches (*e.g.*, if batch sizes would otherwise be too large). Figure 6.5 shows how the assignment can be easily done in the decision support tool. On the left, the product amounts are shown for the different package sizes. On the right, the various production units are shown. As can be seen, certain assignments are not possible (grey areas) because of recipe requirements

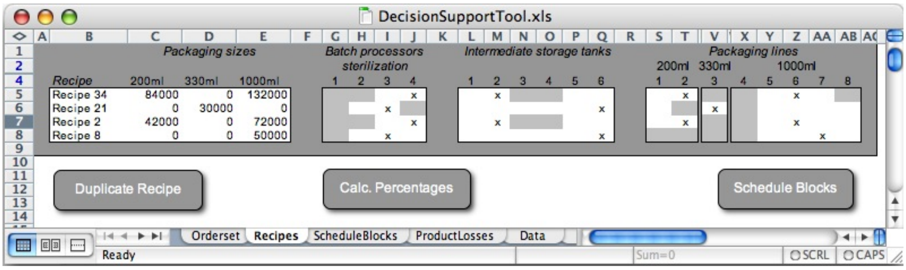

Figure 6.5. Example of the recipe overview and production unit assignments. On the left, recipes and required volumes for different packaging lines are shown (automatically derived from the production orders of Step 1). The remaining part of the screen is used for the assignment of the recipe batches to the various production units (where not all assignments are possible). For example, recipe 34 is to be produced in two different packaging sizes (200ml and 1000ml), and is assigned to batch processor 4, storage tank 2, and packaging lines 2 and 6.

(*e.g.*, a product needs to have a certain treatment in the batch process or can only be stored in a tank which has an agitator). Several additional features are available through buttons below the recipe table.

6.4.3 Step 3 — Schedule blocks

Figure 6.6 shows the result of a deterministic simulation example, based on recipe data, production unit characteristics, and the capacity assignments made in Step 2. The expected realized production is depicted in Gantt charts for each of the recipes, which we call schedule blocks. This includes setups, intermediate cleaning, and stops due to full or empty storage tanks. As this concerns a deterministic simulation study, the production stops of the packaging lines were not modelled with stochastic procedures. To model the efficiency of the packaging lines in a deterministic way, we adjusted the packaging capacity for its average efficiency (for each of the packaging lines). Using these adjusted capacities, the decision support tool creates expected production results.

It is important to note that sequencing decisions were not made in the process to create these so-called schedule blocks. These can affect reuse possibilities for product losses, and should therefore, be considered during the scheduling of the production batches.

We also added the possibility to create a graphical representation of the expected storage level in the intermediate storage tank. This gives additional opportunities to gain insight into the characteristics and interactions of the production process and on the impact of the capacity assignments that were

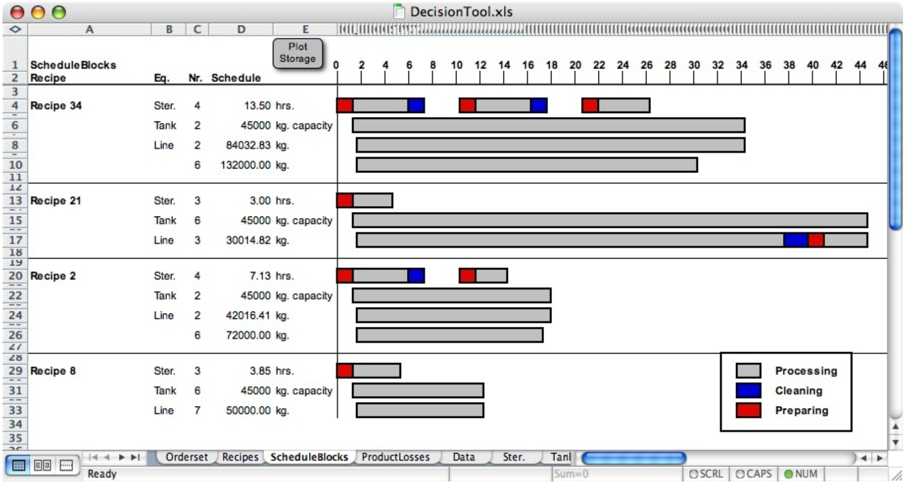

Figure 6.6. Schedule blocks: Gantt charts showing the expected realized production for each of the recipes. This graphically represents the effects of the planning decisions on the expected realized production.

made.

6.4.4 Step 4 — Product losses

Based on the schedule blocks from Step 3, the planning-related amount of product losses can be calculated. From the simulated production runs determined in Step 3, the expected amount of stops and starts of equipment can be calculated and the amount of losses resulting from these is determined. This is summarized in two ways. First, the losses are summed for each of the production units. As mentioned before, the losses calculated are combined with an estimation of the stochastic part of the losses based on the operational time, to create a good overview of the total amount of expected losses. Secondly, the losses are also summed for each of the recipes produced and also combined with an estimation of the stochastic part. This results in a loss percentage per recipe, which can be a very useful insight in the costing aspect of the plant.

6.5 Simulation experiments

Using the decision support tool, we were able to perform simulation studies or what-if analyses to estimate the effects of changes in *e.g.*, scheduling procedures, setup losses, cleaning times, efficiencies, additional capacity, etc.

Based on the current situation in the case study company, we were particularly interested in the effects of an extended planning horizon and the effects of increasing packaging line efficiencies[2].

The experiments described in this section were performed with several weeks of data. Starting from actual schedules, the effects of parameter changes were simulated. In all experiments, close cooperation with the production manager was sought. This was also necessary in some cases, as he would be able to make new production schedules in the experiments concerning the extended planning horizon.

6.5.1 Planning horizon

Currently, production is scheduled on a weekly basis. In the case study company, there was a strong feeling that an extended planning horizon would lead to more efficient batch sizing and would therefore, reduce setups. However, they were not able to quantify this due to the complex interactions in the production system. Larger batches would definitely reduce product losses due to setups, but to what extent it would influence intermediate production stops was unclear.

In our simulation study, we compared a planning horizon of 1, 2, and 4 weeks. We used actual weekly schedules as inputs for the study, and combined these schedules into schedules for 2 weeks and 4 weeks. Due to best-before dates on the end products, a significant number of products is still produced on a weekly basis, even though this results in small, inefficient batches.

To comply with confidentiality, we indexed the results, where the average weekly product loss is set to 100. Figure 6.7 shows that going from a planning horizon of one week to a horizon of two weeks results in a reduction of product losses of nearly 20%. Considering the fact that there were only a few possibilities to combine batches due to the best-before date restrictions, this result is remarkable. Changing the planning horizon to four weeks resulted in an additional 14% improvement, but four weeks might be an unrealistic target in the current competitive environment in the food-processing industry.

[2]Here, efficiency is defined as the total effective time divided by the total production time, where the latter includes unexpected stops, and possible production at lower speeds. Together with the theoretical capacity of the packaging lines, the efficiency is used to determine the total expected production time.

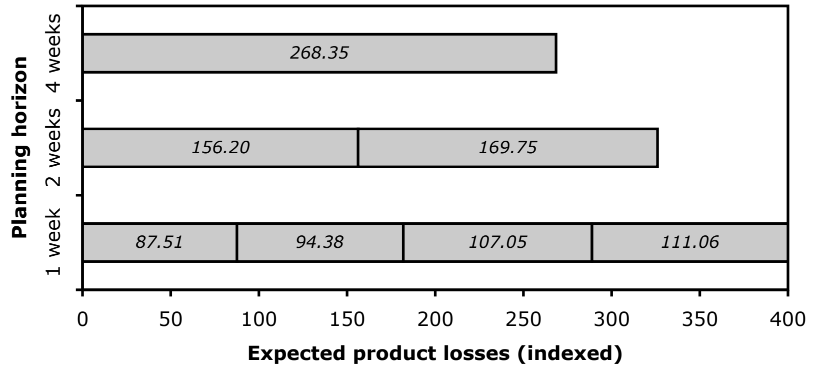

Figure 6.7. Resulting product losses for different planning horizons (average weekly loss is indexed at 100).

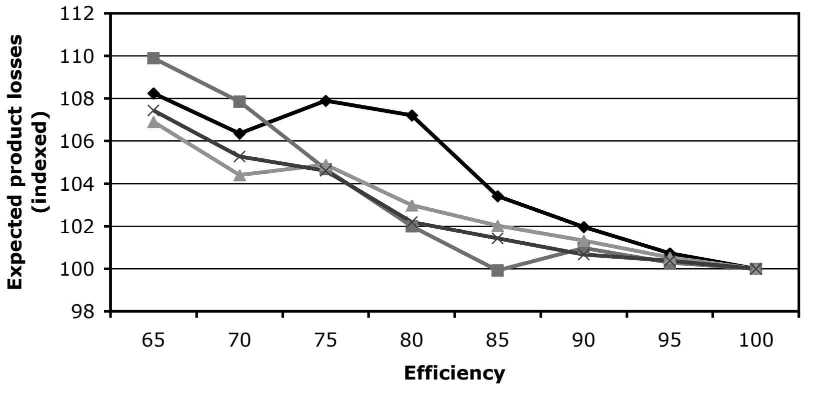

Figure 6.8. Resulting product losses for different efficiencies for four weeks (100% efficiency is indexed at a product loss of 100).

6.5.2 Packaging line efficiency

Here, the expectation of production management is that an increasing efficiency will reduce the number of production stops due to full intermediate storage tanks. However, due to the interactions between the processing and packaging stage, this is not clear. To gain insight into these effects, we simulated four weeks of production under various levels of efficiency. We range the efficiency from 65-100%, to have an extensive range of possible efficiencies. We again indexed the results, and used the results for 100% efficiency as the benchmark value.

The results are shown in Figure 6.8. Experiments show that there is indeed an overall tendency towards less product losses at higher efficiency, but sometimes an increase in efficiency can also lead to an increase of product losses. This is caused by replacing a few long stops of the sterilization process with a larger number of short stops; resulting in more losses due to starting and stopping.

6.6 Conclusions and discussion

This paper discusses the development of a decision support tool for reduction of product losses in the food-processing industry. We created a research framework to collect and analyse data, supporting the development of the tool, and providing insights in the possible scenarios for deterministic simulation studies. The research framework and the development of the decision support tool are illustrated by an application in a dairy processing company.

The current paper is one of the first papers that starts with the idea of reducing the product losses by explicitly relating them to planning decisions. It is also original in the development of a concrete decision support tool that helps to achieve better planning and therefore, helps to prevent or reduce losses. The theoretical value is that the paper helps in better understanding the complexities underlying waste and product losses in food-processing and process industries. Reduction of product losses through improved planning is a fruitful way to improve both the profitability and sustainability of production processes in the food-processing industry.

In the case study, one of the obvious findings is that larger batches, achieved by longer planning horizons, tend to reduce the production losses. However, the relationship turns out to be more subtle then expected due to the interaction effect between packaging lines and their breakdown behaviour, processing lines and the intermediate storage. A longer planning horizon is beneficial for reducing the planning-related amount of product losses. All in all, the tool is able to help the corporate managers to reduce the planning-related losses by nearly 20% by combining only a relatively small amount of batches. But maybe a more important result is the insight gained on the interactions between processing, packaging, and intermediate storage.

In the current application, we limited our focus to a more or less deterministic approach of product losses. Future work might include the stochastic breakdown behaviour of the packaging lines to analyze the effect of strong variation in the amount of product losses and their effects on reusability of the product.

The method as applied in this paper offers a systematic tool to assess the performance of a plant with respect to product losses and the relationship with demand pattern, production batch sizes and planning. It might be obvious that the Excel-tool implementation is case-specific. However, it can easily be adapted to similar production systems and it is built to facilitate use in other situations. We strongly believe that the approach is also applicable for other factories and companies. The research framework and tool structure presented in this paper can be used as guidelines for the case-specific development of decision support tools for reduction of product losses.

In the future, the production manager will also have access to the tool, and will be able to utilize it to evaluate his planning and scheduling decisions. For this, the tool needs some additional development to improve its usability, and then only brief training will be necessary (the implementation in Microsoft Excel greatly improves user acceptance and understanding).

Acknowledgements

The authors would like to thank the company involved in this research for their valuable inputs and the willingness to cooperate in this research project.

CHAPTER 7

Summary and discussion

In this chapter, we outline the results from the individual papers. Also, we look at the the scope and limitations of these papers and what the implications are for future research.

7.1 Summary

The food sector has seen several important developments in recent years. First, competition has become fiercer because of the increased market power of food retailing. Secondly, quality legislation has become more stringent due to a growing concern for food safety throughout the society. Third, sustainable production has become more important, and organizations are held responsible for the environmental performance of their production system.

Concerned for their competitive advantage, food manufacturers increasingly focus on the efficiency of their operations. The developments mentioned are important reasons why good operations management (OM) and especially production planning and control (PPC) have become the key factors in keeping a competitive advantage. Despite a growing amount of research on OM and PPC in the food-processing industry, the field is still lacking behind in comparison with other industries. The overall aim of this thesis is therefore to extend the body of knowledge on OM and PPC in the food-processing industry.

The research presented in this thesis builds on the idea that industry-specific characteristics and configurations have implications for OM and PPC decisions. For example, time-constrained intermediate storage of food products can affect the performance of planning procedures. It is not straightforward that methods that work well in other production situations will also perform well under such perishability constraints. Another example is that increasing market pressure can cause extremely short required lead times, which in turn can force a food manufacturer towards a (partial) make-to-order strategy and accompanying changes in scheduling and storage policies. These two examples illustrate the complex interactions between industry-specific characteristics and OM and PPC decisions.

To study these interactions, we choose to study two-stage food production systems with capacitated intermediate storage. The focus on two stages comes from the notion that food production typically takes place in two steps: processing and packaging. Between the two stages, intermediate products are normally stored in tanks or silos. Analyzing such an archetype system allows us to study a reasonably simple production system, which already contains complex interactions between industry-specific characteristics and OM and PPC decisions.

Chapter 2 starts this thesis with a detailed discussion of the product and production characteristics of the food-processing industry, based on previous research and several case studies. This industry-specific combination of characteristics should be the starting point of any study concerning OM and PPC problems. In the past, PPC has been widely studied in several research areas, resulting in a large number of methods, prescriptions, and approaches. However, the impact on practice seems relatively low, especially concerning production scheduling. Based on ideas about decomposition of scheduling tasks and decomposition of production processes, Chapter 2 develops a methodology for analyzing scheduling problems in the food-processing industry. It combines an analysis of structural (technological) elements of the production process with an analysis of the tasks of the scheduler. Combining these aspects helps to describe, structure, and ultimately solve scheduling problems in food processing. It also forms a basis for improving scheduling and helps in applying scheduling methods developed in the literature.

One of the most striking features of the food-processing industry is the presence of capacity- and time-constrained storage; limited shelf life of intermediate products results in time constraints, next to the —more obvious— capacity constraints. In Chapter 3, we show how various capacity and time constraints influence the performance of a two-stage system with a batch processor in the first stage and packaging lines in the second stage, linked by storage tanks. Using simulation, we demonstrate the impact of several well-known scheduling rules. The success of these rules depends on the performance measure used, and is significantly affected by the variation in packaging times. Due to blocking and starvation effects caused by the capacitated intermediate storage, the longest-processing-time-first (LPT) rule is able to maximize the total production volume per day —contrary to the common sense in operations management. Furthermore, we show that relaxing the capacity constraint by adding one single intermediate storage tank already has considerable positive effects in terms of delivery performance —but also negatively affects the amount of product losses in the system. Finally, we conclude that the optimal setup frequency for batches (which corresponds to batch sizes) in the first stage is dictated by the storage time constraint. An important managerial insight based on these results is that both blocking and starvation negatively affect performance (in terms of production time), but only blocking causes product losses.

In practice, there are normally more intermediate products than intermediate storage tanks. This means some products have to share storage space. But, in order to meet the short lead times required by the current competitive market, storage tanks are sometimes dedicated to a single product to be able to package this product on demand, ensuring the required lead time. Dedication of storage is a widely used practice, and not only because of the lead-time reduction. It can also be the consequence of limited connectivity of equipment, or the result of planning and scheduling habits. In Chapter 4, dedicated and flexible intermediate storage is studied, combined with the prioritization of products in the packaging stage. Both these issues are ways to cope with the required lead times in the food-processing industry. The chapter aims at investigating the fundamental effect of prioritization and dedicated storage in a two-stage production system, for various product mixes. Simulation results show the improvements in performance for a prioritized product, as well as the negative effects for the remaining products (that have to share intermediate storage). The results also show that these effects decrease with more storage tanks, and increase with more products. Finally, by analyzing several product-mix scenarios, we illustrate that the dedication decision causes irregularity in the production schedules, leading to increased blocking and starvation effects. The results also indicate that the share of the prioritized product in the product mix determines the amount of blocking and starvation caused by the prioritization (and related dedication). For both relatively low and relatively high shares for the prioritized product, blocking and starvation effects increase, which leads to lower efficiency of equipment. In an industry where utilization already is high, this is obviously an undesirable situation.

Due to the increasingly fierce competition in the food industry, we see regular introductions of new products and/or special offers. Often, such an introduction or promotional effort affects the demand for other products or packaging types. This means individual product demands are correlated. In Chapter 5, we study the effect of such correlated demand. More specifically, the aim of this chapter is to study the effect of product mix variability and correlated demand in a two-stage food production system. Correlation of demand can be found on two levels: the product level and the package level, and can be both positive (affecting other product or package types in the same direction) and negative (affecting other product or package types in the opposite direction). Results from a simulation study show that increasing correlation on the product level results in an increase in average lead times. For correlation on the package level, the increase is also found, albeit slightly smaller. Also, there do not appear to be interactions between the two levels of correlation. Similar results are found for the average amount of product losses. Increased demand variability strengthens the effects found. Overall, the analysis shows that demand correlations are an important consideration in decisions involving the product mix (e.g., new product introductions, order acceptance), and the consideration should include both levels of correlation as they have about the same impact on lead times and product losses.

Finally, Chapter 6 focuses on reduction of product losses in the production process. In food processing, losses are an inherent part of production; raw materials are normally lost in setups, cleaning procedures, and other process interruptions. Considering the fierce competition in the food sector, the reduction of such losses is of great importance for improving profitability. Furthermore, it is also a major step towards sustainable operations. In Chapter 6, we contribute to this topic by developing a research framework and a decision support tool for analyzing the effect of planning decisions on the amount of product losses in the food-processing industry. The research framework aims to collect and analyze data, supporting the development of a decision support tool that helps to investigate different scenarios for the planning decisions and production parameters. The first steps in the framework are the analysis of (i) process characteristics, (ii) demand characteristics, and (iii) production disturbances. The results from these analyses can subsequently be used in the development of a decision support tool. In Chapter 6, the analysis and tool development are applied in a case study in the dairy industry, where the Excel-based tool was able to reduce the planning-related losses with nearly 20%. Next to the reduction of product losses, maybe an equally important result is the insight gained on the interactions between processing, packaging, and intermediate storage (*e.g.*, when equipment has to stop due to full or empty intermediate storage). The framework and tool can easily be adapted to other situations.

7.2 Discussion

The main aim of this thesis was to improve the knowledge on the interactions between industry-specific characteristics and OM issues within typical two-stage food production systems with capacitated intermediate storage. This aim was translated into three research questions. The first question concerned the effects of capacity and time constraints on the intermediate storage. This issue was addressed in Chapter 3 and 4 (and was also illustrated in the case study in Chapter 6). The second research question, the effects of high product mix variability and lead-time reductions were addressed in Chapter4 and 5. Finally, the third research question specifically concerned the influence of planning decisions and process configurations on the realization of product losses in the production process, and was dealt with in the case study in Chapter 6. The results presented in this thesis provide insights in the operational performance of two-stage food production systems with intermediate storage. This performance not only entails competitiveness (through the insights on lead time performance), but also sustainability (through the insights on product losses).

7.2.1 Reflections on results

In a large part of this thesis, results are based on studies of fairly basic production situations. This choice was made to keep models simple, yet still large enough to contain fundamental interactions. This way, the results provide a basic understanding of the complex interactions found in two-stage food production systems with intermediate storage. In the various studies, specific assumptions were made to minimize the number of influencing factors and focus the analysis on the subject of study. Adding more factors to the models (for instance sequence-dependent setup times) would increase the interactions between factors, and make it difficult to draw conclusions on the most important factors chosen in this research.

The results presented in this thesis focus on operational performance (in lead times and product losses). This does not necessarily mean that the insights gained are limited to operational performance. For instance, the results can also be used in the (re)design of food production systems; numerous important decisions have to be made in this stage, including the connectivity of equipment, or the choice between a few large storage tanks or multiple small ones. These choices are often related to investment decisions based on trade-offs between additional process capacity and flexibility on the one hand and operational costs on the other hand.

Although the issues studied in this thesis were inspired by and are typically found in the food-processing industry, other industries might also face similar issues. To what extent the results are usable in other environments depends on the characteristics of the production process. This research has focused on two-stage processes with intermediate storage. Furthermore, the products get their discrete form in the second stage of the production process. This means that for the most part, the product does not have a shape or form and is to be stored in tanks or silos. If these characteristics are present in other production situations, the insights from this thesis can be used. Obviously, this holds for most food manufacturers, but likely also for numerous other process industries.

7.2.2 Future research possibilities

This thesis has specifically focused on a number of characteristics (*e.g.*, shelf-life constraints, management of intermediate storage tanks) found in the food-processing industry. In the previous chapters, specific suggestions for future research have already been made. Here, several more general guidelines are presented.

Next to the food-specific characteristics discussed in this thesis, several other characteristics (as outlined in Chapter 2) make interesting topics for further research. Especially, a good understanding of the various sources of uncertainty found in food production (concerning processing yields, raw material quantity or arrival times, etc.) would be a interesting and valuable extension to this research. In the design of production systems —including intermediate storage facilities— one should be able to take these factors into account. Two different directions can be identified for this proposed further research. First, similar small production situations could be utilized to study the effects of other important characteristics of the food-processing industry, like variable processing yields. Secondly, another research direction would be to study such characteristics in more complex production situations, although this would likely result in very system-specific results, which was to some extent already the case in the basic systems used in Chapter 3 to 5 of this thesis. Studying more complex (or even real-life) situations would make it possible to show in which specific contexts the results from this research are the most dominant.

The production situations studied in this thesis all have full connectivity, *i.e.*, all equipment is connected. In practice, this is often not the case; production systems often consist of a collection of (weakly connected) groups of fully connected resources. This could mean that real-life situations are just a collection of smaller systems (close to our archetype production system), but it could also mean a distinction between certain strongly connected resources and a number of weakly connected groups of resources. This would also lead to different kinds of system interactions, which are an interesting topic for further study.

Due to the increasing competition in the food sector, market characteristics are becoming a very important factor. New product introductions are common, and product ranges have grown over the last decade. Production processes have not changed as much in this period, which often led to increasing unbalances between the product mix and the production system that is supposed to support it, resulting in production inefficiencies. The possible interactions and relationships between product design and process design have hardly been considered in the literature, but seem to be an important factor in performance realization. The correlated demands discussed in Chapter 5, and the product losses issue discussed in Chapter 6 are related to this theme, but there are many more aspects that warrant further investigation.

Future research could also be conducted to develop decision tools to help production managers understand the interactions (and their magnitudes) in their specific production system. From the experiences with the simulation tool presented in Chapter 6, it was clear that interactive models in an easy-to-use environment could provide production managers and planning staff with a lot of additional insights in the dynamics of their production system. In Chapter 6, modelling was done in Microsoft Excel, which is already familiar to most potential users and therefore reduces barriers for usage. More specifically for the tool presented in Chapter 6, future work could also include a different approach to the breakdown behaviour in the packaging stage. This was based on a deterministic model, but could also be approached stochastically to be able to gain a deeper understanding in the interactions between processing, packaging and intermediate storage. Furthermore, the results in Chapter 6 are partially case-specific. Although the tool is built to facilitate reuse in other situations, further research could lead to more general modelling tools for the analysis of product losses (or other performance measures) in the food-processing industry. Part of this research could possibly apply to the process industry in general.

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Samenvatting (Summary in Dutch)

In de voedingsmiddelenindustrie hebben zich een aantal belangrijke ontwikkelingen voorgedaan. Op de eerste plaats is de concurrentie toegenomen door de sterk groeiende marktinvloed van de detailhandelsketens. Op de tweede plaats is de wetgeving op het gebied van kwaliteit strenger geworden door een toename van de zorg omtrent voedselveiligheid. Tenslotte wordt duurzame productie steeds belangrijker, ook omdat organisaties verantwoordelijk worden gehouden voor milieutechnische prestaties van hun productiesystemen.

Om hun concurrentiepositie te versterken, richten bedrijven in de voedingsmiddelenindustrie zich steeds meer op efficiëntie van hun processen. Hierin vervullen *Operations Management* (OM) en *Production Planning and Control* (PPC) een sleutelrol. Ondanks de toename in onderzoek naar OM en PPC in de voedingsmiddelenindustrie, blijft dit nog steeds achter in vergelijking met andere industrieën. Het globale doel van dit proefschrift is dan ook het uitbreiden van de aanwezige kennis op het gebied van OM en PPC in de voedingsmiddelenindustrie.

Het onderzoek wat gepresenteerd wordt in dit proefschrift bouwt voort op het idee dat specifieke industrie-afhankelijke kenmerken belangrijke factoren zijn bij beslissingen omtrent OM en PPC. Een voorbeeld is dat beperkte houdbaarheid van voedingsmiddelen invloed heeft op de bruikbaarheid van planningsmethoden. Het is niet meteen duidelijk of methodes die in andere gevallen goed werken, ook goed werken bij beperkte houdbaarheid van producten. Een ander voorbeeld is dat de toegenomen marktinvloed van de detailhandel kan leiden tot extreem korte gewenste levertijden, wat er weer toe kan leiden dat fabrikanten (deels) op voorraad zullen moeten produceren. Dit leidt tot vernieuwing van hele planningsmethodieken en opslagprocedures. Deze voorbeelden illustreren de complexe interacties tussen enerzijds specifieke industrie-afhankelijke kenmerken en anderzijds beslissingen op het gebied van OM en PPC.

Om deze interacties te bestuderen, is er voor gekozen om een productiesysteem met twee productiestappen en beperkte tussenopslag te bestuderen. Deze keuze komt voort uit het feit dat de productie van voedingsmiddelen

over het algemeen uit twee stappen bestaat: het verwerken van de grondstoffen tot product en het verpakken van het product. Tussen deze twee stappen wordt het product normaal gesproken opgeslagen in tanks of silos. Door het bestuderen van deze grondvorm, zijn we in staat een relatief simpel productiesysteem te analyseren, dat toch relevante interacties bevat tussen industrie-afhankelijke kenmerken en OM/PPC beslissingen.

Dit proefschrift begint in hoofdstuk 2 met een gedetailleerd overzicht van de product- en productiekenmerken in de voedingsmiddelenindustrie, gebaseerd op eerder onderzoek en diverse praktijksituaties. Deze collectie specifieke kenmerken van de voedingsmiddelenindustrie is het startpunt van elk onderzoek met betrekking tot OM en PPC vraagstukken. In het verleden heeft onderzoek naar PPC in het algemeen geresulteerd in een uitgebreid arsenaal aan methodes en procedures. Echter, het aantal praktische toepassingen hiervan lijkt achter te blijven, in het bijzonder waar het de detailplanning van productiesystemen betreft. Op basis van ideeën over decompositie van planningsproblemen en productieprocessen wordt in hoofdstuk 2 een methode ontwikkeld waarmee planningsproblemen in de voedingsmiddelenindustrie kunnen worden geanalyseerd. De methode combineert een analyse van structuurkenmerken van het productieproces met een analyse van taakkenmerken van de productieplanner. De combinatie van deze elementen helpt in het beschrijven, structureren, en uiteindelijk het oplossen van planningsproblemen in de voedingsmiddelenindustrie. Het creëert ook een basis voor het toepassen van methodes en procedures uit de literatuur en het verbeteren van de huidige planning.

Eén van de meest kenmerkende eigenschappen van de voedingsmiddelenindustrie is de aanwezigheid van capaciteits- en tijdsbeperkingen bij de tussenopslag. Beperkte houdbaarheid van producten resulteert in de tijdsbeperkingen, naast de meer voor de hand liggende capaciteitsbeperkingen als gevolg van een beperkte hoeveelheid opslagtanks, met per tank een beperkte inhoud. In hoofdstuk 3 laten we zien hoe verschillende capaciteits- en tijdsbeperkingen de prestaties van een typisch productieproces beïnvloeden. Met behulp van simulatiestudies wordt het effect van verschillende bekende planningsregels gedemonstreerd. De effectiviteit van deze regels is afhankelijk van de prestatiemaatstaf, en wordt beïnvloed door de mate van variatie in de verpakkingstijden. Doordat er bij de tussenopslag blokkering en leegloop optreden, blijkt de langste-bewerkingstijd-eerst (LPT) regel het beste te presteren indien men het totale productievolume per dag wenst te maximaliseren; dit in tegenstelling tot de algemene opvattingen binnen OM. Verder blijkt dat het toevoegen van een enkele tank bij de tussenopslag leverprestaties aanzienlijk verbetert, maar dat dit slechtere prestaties oplevert in termen van productverliezen in het productieproces. Tenslotte concluderen we dat de optimale omstelfrequentie in de eerste stap van het productieproces (wat tevens gerelateerd is aan batchgroottes) opgelegd wordt door de houdbaarheidsbeperkingen. Een belangrijk praktisch inzicht wat uit deze resultaten volgt is dat blokkering én leegloop bij de tussenopslag tot slechtere prestaties leiden (in termen van levertijden), maar alleen blokkering leidt tot productverliezen.

Als gevolg van het groeiende aantal verschillende producten in de voedingsmiddelenindustrie, zien we in de praktijk vaak dat er meer producten in de tussenopslag opgeslagen worden dan dat er opslagtanks zijn. Om in deze situatie toch te voldoen aan de korte levertijden die vanuit de markt gevraagd worden, moeten er soms een aantal opslagtanks voor langere tijd worden toegewezen aan een bepaald product, zodat deze dan uit voorraad verpakt kunnen worden en daarmee de gevraagde levertijd gehaald kan worden. Deze vaste toewijzing van opslagtanks komt in de praktijk veel voor. Niet alleen om levertijden te verkorten, maar ook vanwege beperkte verbindingen tussen productiematerieel en opslagtanks, of vanwege gewoontes in productieplanning en -beheersing. In hoofdstuk 4 wordt het onderscheid tussen vast en flexibel toegewezen tussenopslag bestudeerd, in combinatie met prioritering van producten in het verpakkingsstap van het productieproces. Beide onderwerpen hebben te maken met het realiseren van de veelvoorkomende gewenste korte levertijden in de voedingsmiddelenindustrie, en worden in hoofdstuk 4 bekeken voor verschillende situaties met betrekking tot het productassortiment. Simulatiestudies laten verbeterde levertijden zien voor de geprioriteerde producten, maar ook verslechterde prestaties voor de resterende producten (die ook tussenopslag moeten delen). De resultaten laten ook zien dat deze effecten kleiner worden naarmate er meer tussenopslag is, en groter worden naarmate er meer producten zijn. Tenslotte wordt door analyse van verschillende scenarios voor het productaanbod aangetoond dat de vaste toewijzing van tussenopslag zorgt voor onregelmatigheden in de productieplanning, waardoor meer blokkering en leegloop ontstaat. De resultaten suggereren ook dat het aandeel van het geprioriteerde product in het productaanbod (en de daarmee samenhangende vaste toewijzing van tussenopslag) een belangrijke factor is voor de hoeveelheid blokkering en leegloop. In het geval van een laag, maar ook in het geval van een hoog aandeel, treedt er relatief veel blokkering en leegloop op. Dit leidt uiteindelijk tot een lagere efficiëntie van de batchprocessen en de verpakkingslijnen, wat een onwenselijke situatie is, vooral in een sector waar de bezettingsgraad over het algemeen hoog is.

Als gevolg van de toenemende concurrentie in de voedingsmiddelenindustrie, zien we vaak promotionele activiteiten of introducties van nieuwe producten. Meestal leidt dit ook tot veranderingen in de vraag naar andere producten of verpakkingen, wat betekent dat de vraag naar individuele producten gecorreleerd is. De effecten hiervan worden in 5 bestudeerd. Het hoofdstuk richt zich naast correlaties in de vraag naar producten op de mate van variabiliteit in de vraag. De correlaties kunnen op twee vlakken bestaan: op productniveau en op verpakkingsniveau, en kunnen beide positief of negatief zijn. Bij positieve correlatie varieert de vraag naar andere producten of verpakkingen in dezelfde richting, en bij negatieve correlatie in de tegenovergestelde richting. De resultaten van een simulatiestudie laten zien dat een toename in correlatie op het productniveau een verlenging van levertijden tot gevolg heeft. Voor correlatie op verpakkingsniveau wordt deze relatie ook gevonden, al is deze iets minder sterk. Daarnaast lijken er geen interacties te bestaan tussen de twee niveaus waarop correlatie kan bestaan. Soortgelijke resultaten worden gevonden in het geval van prestaties in de vorm van de hoeveelheid productverliezen. Een toename van de mate van variabiliteit in de vraag versterkt de gevonden effecten. In het algemeen laten de analyses zien dat correlaties in de vraag een belangrijke factor zijn in beslissingen omtrent het productassortiment (zoals bijvoorbeeld de introductie van nieuwe producten, of de acceptatie van bestellingen). Bij deze beslissingen moet ook rekening gehouden worden met correlaties op product- en verpakkingsniveau, omdat beide een sterke invloed hebben op levertijden en productverliezen.

Vervolgens wordt in hoofdstuk 6 de nadruk gelegd op de vermindering van productverliezen in een productieproces. In de voedingsmiddelenindustrie zijn deze verliezen een inherent onderdeel van de productie; het is gebruikelijk dat er grondstof verloren gaat bij het omstellen, reinigen of anderszins onderbreken van het productieproces. In het licht van de hevige concurrentie in deze sector, en de hierdoor kleiner wordende marges, is de reductie van productverliezen een belangrijke stap in het verbeteren van de winstgevendheid. Daarnaast is het een zeer relevante factor in de duurzaamheid van productiesituaties in de voedingsmiddelenindustrie. In hoofdstuk 6 dragen we bij aan deze onderwerpen met de ontwikkeling van een onderzoeksraamwerk en een beslissingsondersteunend model voor het analyseren van de relatie tussen planningsbeslissingen en de hoeveelheid productverliezen. Het onderzoeksraamwerk richt zich op het verzamelen en analyseren van gegevens met betrekking tot (i) proceskenmerken, (ii) kenmerken van de vraag naar producten, en (iii) productieonderbrekingen. De resultaten van deze analyses kunnen dan vervolgens gebruikt worden in de ontwikkeling van het beslissingsondersteunende model, waarmee verschillende scenarios met betrekking tot planningsbeslissingen en productieparameters worden gesimuleerd. In hoofdstuk 6 zijn het raamwerk en het model tevens toegepast in een praktijksituatie in de zuivelindustrie. Met behulp van een Excel-applicatie op basis van het model was het mogelijk de productverliezen die gerelateerd waren aan planningsbeslissingen met bijna 20% te verminderen. Naast deze reductie van productverliezen zijn ook veel inzichten verkregen in de interacties tussen de twee productiestappen en de tussenopslagmogelijkheden. Hier kan bijvoorbeeld gedacht worden aan het moeten stilzetten van batchproces of verpakkingslijn als gevolg van volle of lege tussenopslag. Het onderzoeksraamwerk en het beslissingsondersteunende model kunnen ook toegepast worden in andere, vergelijkbare, situaties.

De resultaten die gepresenteerd worden in dit proefschrift richten zich vooral op operationele prestaties (in termen van levertijd en productverliezen) van productiesystemen in de voedingsmiddelenindustrie. Dit betekent niet dat de verworven inzichten zich beperken tot deze operationele prestaties. De resultaten kunnen bijvoorbeeld ook gebruikt worden in het (her)ontwerp van productiesystemen; waar veel belangrijke beslissingen genomen worden omtrent de aan te leggen verbindingen tussen materieel en het aantal en de grootte van tanks voor tussenopslag. Daarnaast is de problematiek die in dit proefschrift aan bod komt wel geïnspireerd door en gebaseerd op de voedingsmiddelenindustrie, maar dat wil niet zeggen dat andere industrieën niet soortgelijke problematiek kennen. In hoeverre de resultaten van dit proefschrift bruikbaar zijn in andere omgevingen is afhankelijk van de kenmerken van de desbetreffende productieprocessen.